

NAVAL POSTGRADUATE SCHOOL

Monterey, California



DISSERTATION

**NEW DATA FUSION ALGORITHMS FOR
DISTRIBUTED MULTI-SENSOR MULTI-TARGET
ENVIRONMENTS**

by

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September 1999

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DTIC QUALITY INSPECTED 4

19991029 083

REPORT DOCUMENTATION PAGE			Form Approved OMB No. 0704-0188	
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time reviewing instructions, searching existing data sources gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188), Washington, DC 20503.				
1. AGENCY USE ONLY (Leave Blank)		2. REPORT DATE September 1999		3. REPORT TYPE AND DATES COVERED Doctoral Dissertation
4. TITLE AND SUBTITLE NEW DATA FUSION ALGORITHMS FOR DISTRIBUTED MULTI-SENSOR MULTI-TARGET ENVIRONMENTS			5. FUNDING NUMBERS	
6. AUTHOR(S) Ashraf Mamdouh Abdel Aziz				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING/ MONITORING AGENCY NAME(S) AND ADDRESS(ES)			10. SPONSORING/ MONITORING AGENCY REPORT NUMBER	
11. SUPPLEMENTARY NOTES The views expressed in this dissertation are those of the author and do not reflect the official policy or position of the Department of Defense or the United States Government.				
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution is unlimited			12b. DISTRIBUTION CODE	
13. ABSTRACT (Maximum 200 words) Multisensor data fusion combines data from multiple sensor systems to achieve improved performance and provide more inferences than could be achieved using a single sensor system. One of the most important aspects of data fusion is data association. This dissertation develops new algorithms for data association, including measurement-to-track association, track-to-track association and track fusion, in distributed multisensor-multitarget environment with overlapping sensor coverage. The performance of the proposed algorithms is compared to that of existing techniques. Computational complexity analysis is also presented. Numerical results based on Monte Carlo simulations and real data collected from the United States Coast Guard Vessel Traffic Services system are presented. The results show that the proposed algorithms reduce the computational complexity and achieve considerable performance improvement over those previously reported in the literature.				
14. SUBJECT TERMS Fuzzy Techniques, Multi-sensor Multi-target Data Fusion, Data Association, Track-To-Track association, Track Fusion, Distributed Decision Fusion			15. NUMBER OF PAGES 247	
			16. PRICE CODE	
17. SECURITY CLASSIFICATION OF REPORT Unclassified		18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified		19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified
				20. LIMITATION OF ABSTRACT UL

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ABSTRACT

Multisensor data fusion combines data from multiple sensor systems to achieve improved performance and provide more inferences than could be achieved using a single sensor system. One of the most important aspects of data fusion is data association. This dissertation develops new algorithms for data association, including measurement-to-track association, track-to-track association and track fusion, in distributed multisensor-multitarget environment with overlapping sensor coverage. The performance of the proposed algorithms is compared to that of existing techniques. Computational complexity analysis is also presented. Numerical results based on Monte Carlo simulations and real data collected from the United States Coast Guard Vessel Traffic Services system are presented. The results show that the proposed algorithms reduce the computational complexity and achieve considerable performance improvement over those previously reported in the literature.

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LIST OF SYMBOLS

- \mathbf{y} observation (measurement) vector
- $\hat{\mathbf{y}}$ predicted measurement vector
- $\tilde{\mathbf{y}}$ residual error of measurement vector (innovation)
- \mathbf{x} state vector
- $\hat{\mathbf{x}}$ predicted state vector
- $\tilde{\mathbf{x}}$ residual error of state vector
- σ measurement standard deviation
- σ_r residual standard deviation
- σ_p predicted standard deviation
- \mathbf{G}_k gating constant vector at scan k
- \mathbf{G}_0 maximum likelihood gate
- \mathbf{S} residual covariance matrix
- β_{F_t} false target density
- β_{N_t} new target density
- p_d detection probability
- P_G probability of a valid observation satisfying a gate
- d distance metric
- r_{xy} correlation coefficient between two measurement vectors \mathbf{x} and \mathbf{y}
- S_{xy} association coefficient between two measurement vectors \mathbf{x} and \mathbf{y}
- $\bar{\mathbf{x}}$ mean value of vector \mathbf{x}
- M total number of measurements
- L_k likelihood function at scan k
- f_{er} probability density function of residual error
- N_u number of updated detections
- \mathbf{K} standard Kalman filter gain

- β_{ij} probability that observation j comes from target i
- \mathbf{F} state transition matrix
- \mathbf{H} measurement matrix
- T_s sampling interval
- $\{w(k)\}$ measurement noise sequence
- \mathbf{C}_k covariance matrix of measurement noise
- $\{g(k)\}$ plant noise sequence
- \mathbf{Q}_k covariance matrix of plant noise
- \mathbf{P}_i covariance matrix of an estimate \mathbf{x}_i
- \mathbf{P}_{ij} cross-covariance between two estimates
- \mathbf{X}_f fused estimate
- \mathbf{P} covariance of fused estimate
- $\mu_A(x)$ membership function
- μ_{ij} degree of membership of data i in cluster j
- c number of clusters
- $S_i(k)$ speed of target i at scan k
- $P_i(k)$ position of target i at scan k
- m fuzzification constant
- $R(i, j)$ fuzzy correlation variable between observation i and track j
- N_R number of fuzzy IF-THEN rules
- ℓ number of linguistic variables
- $\pi_x(x)$ possibility distribution
- $f_x(x)$ probability distribution
- $C(\pi, P)$ consistency measure between possibility and probability
- θ bearing information
- \mathbf{R}_i report of track i
- \mathbf{R}_{ij} report from sensor j due to observing target i

- Δ_i resolution vector of sensor i
- n_a total number of attributes
- n_s number of sensors
- n_t number of targets
- n_r number of reports before fusion
- n_{rf} number of reports after fusion
- H_i hypothesis i
- H_1 hypothesis when two tracks are the same
- H_0 hypothesis when two tracks are different
- \mathbf{U} similarity matrix
- D_i association decision based on resolution of sensor i
- D_g global association decision of the fusion center
- $CORR(i, j)$ correlation between two reports i and j
- \mathbf{R}_f fused report (track)
- \mathbf{R}_{DOM} dominant track
- Δ_{DOM} resolution of dominant track
- Δ_{ij} cross-resolution between two sensors (systems)
- μ_{CR} degree of membership of cross-resolution
- μ_{CC} degree of membership of cross-correlation between two reports
- e mean square error
- σ_r standard deviation of range measurement error
- σ_θ standard deviation of bearing measurement error
- $\sigma_{r\ell}$ standard deviation of range error due to ionosphere layer
- $\sigma_{\theta\ell}$ standard deviation of bearing error due to ionosphere layer
- u_i decision of sensor i
- u_0 global decision of the fusion center
- p_f sensor false alarm probability

- p_F global false alarm probability of the fusion center
- p_d sensor detection probability
- p_D global detection probability of the fusion center
- $f(\mathbf{y}|H_i)$ probability density function of \mathbf{y} under hypothesis H_i
- L_i likelihood ratio test of sensor i
- λ_i threshold of sensor i
- λ_0 threshold of the fusion center (centralized detection)
- $Var\{\mathbf{y}\}$ variance of observation vector \mathbf{y}
- SNR Signal to Noise Ratio
- PRI Pulse Repetition Interval
- RF Radio Frequency
- PW Pulse Width
- $MSMT$ Multisensor-Multitarget
- $NNSF$ Nearest-Neighbor Standard Filter
- PDA Probabilistic Data Association
- $JPDA$ Joint Probabilistic Data Association
- MHT Multiple Hypothesis Tracking
- $MTCS$ Multi-Track Common Source
- $USCG$ United States Coast Guard
- VTS Vessel Traffic Services
- $FLIR$ Forward Looking Infrared
- ROC Receiver Operating Characteristic
- FCM Fuzzy Clustering Means
- GPS Global Position System
- SR Standard Routes
- $Tdbm$ Track Data Base Manager
- AND AND fusion rule

- *MAP* Maximum *A Posteriori* Probability
- *OR* OR fusion rule
- *IFF* Identification Friend or Foe
- *ESM* Electronic Support Measures
- *MSE* Mean Square Error
- $\phi(x)$ The complimentary error function defined as $\int_x^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz$

DEDICATION

*To my mother, my daughters, Menat and Mariem, my
brothers, and the memory of my father*

ACKNOWLEDGMENTS

(Thanks to God Before and After)

I would like to express my thanks and deepest gratitude to several people. Most importantly, I wish to pay deep tribute to my father Mamdouh Abdel Aziz, who died during the course of this work. I truly miss him and thank him for everything. I would like to thank my mother and my daughters, Menat and Mariem, whom I absolutely adore, for their ever present unconditional love and support.

I wish to express my thanks and deepest gratitude to my dissertation advisors, Professors Murali Tummala and Roberto Cristi, for their guidance, support, knowledge, and valuable time and experience. No words can express my feeling and respect for their constructive criticism at every stage of this work. They have been great friends. I also thank the remaining members of my committee, Professors Robert B. McGhee, David C. Jenn, and Fariba Fahroo, for their advice, comments, and valuable discussions. Special thanks to Professor Robert G. Hutchins for his excellent course notes in EC3310.

I also wish to thank Professors ElAyadi, Eweda, and ElBasiouny. They have played a big part in my development during my study in the Military Technical College (Egypt). They have been true professionals and very supportive.

Finally, I would like to thank my best friends Capt. Engineer Waleed Mamdouh (my brother), Mr Gaber Abdel-Satar (my cousin), Mr Sayed Shebl (my uncle), Dr. Hesham El-Deeb, Dr. Mahmoud Wahdan, Dr. Khaled Morsy, Dr. Nabil Khalil, Dr. Khaled Shehata, Dr. Hazem Fahmy, Dr. Adnan ElShafei, Dr. Osman, Major Engineer Osama Kamal, Mr Anter Galal, Mr Mohamed Abou Taleb, Mr Bahaa Saad, and Engineer Hussein ElSewisy (Egypt) for their encouragement.

I. INTRODUCTION

In recent years, multisensor data fusion has received considerable interest in both military and civilian applications. Multisensor data fusion is a process in which data from multiple, diverse sensors, sensing multiple objects, are combined to yield improved accuracy and more inferences than could be achieved using a single sensor system. Data refers to the measurements (attributes) obtained by the sensors, and fusion is the process of combining these multiple measurements into a single measurement of the sensed object. Currently, multisensor data fusion is used extensively in military applications for target tracking [Ref. 1, 2, 3, 6, 86]. Fusion for target tracking involves association and estimation [Ref. 8, 130]. In multisensor-multitarget (*MSMT*) environment, the sensors do not provide any information about the origins of the measurements, i.e., the association between the measurements and the targets is not known *a priori*. Thus the most important function in *MSMT* data fusion is the association of the measurements to the targets before any estimates can be made from the measurements. Data association is responsible for partitioning the measurements into sets that could have originated from the same targets.

A. BACKGROUND

There are two major types of data association in *MSMT* environments with overlapping sensor coverage [Ref. 7, 142, 157, 161]: measurement-to-track association and track-to-track-association. In measurement-to-track association, measurements are selected from many to update the tracks (implemented at the sensor level). In track-to-track association, all the measured tracks are processed in a data fusion center to decide whether or not two tracks represent the same target (implemented at the fusion center level). Track-to-track association correlates redundant tracks that are provided from multiple sensors on the same targets into a unique set of tracks that represents the actual number of targets. The fusion center combines two or more tracks when it is decided that they represent the same target. This problem

is called track fusion [Ref. 116, 119, 120, 133, 137]. This dissertation addresses the problem of data association, including measurements-to-track association, track-to-track association, and track fusion, in distributed multisensor-multitarget multiple-attribute environment with overlapping sensor coverage.

There are two main categories of data association in *MSMT* environment: algorithmic and nonalgorithmic [Ref. 58]. The algorithmic category is based on nearest-neighbor association in which one measurement, at most, can be used, according to some similarity measure, to update a track and all-neighbor association in which a track may be updated using a contribution from more than one measurement according to some scores. The nonalgorithmic category is based on neural network and fuzzy logic techniques.

The optimum nearest-neighbor data association technique is derived in [Ref. 3, 15, 26] by defining a likelihood function and selecting the association that maximizes the likelihood expression. The evaluation of the maximum likelihood expression in each scan for all possible observation-to-track combinations is computationally infeasible. Instead, suboptimal nearest-neighbor association techniques are developed. Blackman [Ref. 3] and Rong Li [Ref. 146] considered different examples of simple and suboptimal nearest-neighbor association techniques using different association measures.

Bar-Shalom [Ref. 3, 7, 31] developed the nearest-neighbor standard filter in which data association of measurements to tracks is based on the maximum likelihood function of the residual error. Bar-Shalom and Fortman [Ref. 7] developed the two main techniques of all-neighbor data association: probabilistic data association (*PDA*) and joint probabilistic data association (*JPDA*) techniques. In these techniques, the updated estimate for a given track may contain contributions from more than one measurement with some association probabilities [Ref. 159]. The *JPDA* method is identical to the *PDA* except that the association probabilities are computed using all measurements and all tracks [Ref. 13, 18, 27, 28, 30]. The calculation of the probability scores is quite complex and computationally intensive. Thus

suboptimal solutions are developed. The only difference among the optimal solution of *PDA* and *JPDA* and the suboptimal solutions is the method of calculating the probability scores. A large number of suboptimal solutions has been developed in the literature [Ref. 29, 109, 110, 129, 145, 160].

The interacting multiple model joint probabilistic data association is another version of the *JPDA* [Ref. 78, 79, 141]. The interacting multiple model *JMPDA* is a soft-decision zero back scan association approach, which combines in a probabilistic score several observations and several dynamic models to determine the target state estimate. Molnar et al. [Ref. 64] described an iterative procedure for time-recursive *MSMT* tracking based on an expectation-maximization algorithm. This algorithm depends on the maximum *a posteriori* (*MAP*) estimate of the target state. The algorithm is proved to be effective compared to *JPDA* approach at the expense of additional computations.

The multiple hypothesis tracking techniques are hard-decision multiscan association techniques [Ref. 3, 7, 141] in which the association process depends on the current as well as the past data. This approach is recognized as the theoretically best approach for the *MSMT* tracking problem under ideal modeling assumptions, yet it requires a considerable amount of computation and memory. Outputs from multiple hypothesis tracking techniques are typically a list of hypotheses that can be ranked by their probability estimates. The number of hypotheses grows when a new data set is received. The final assignment of observations to tracks is determined according to the maximum value of the association probability among all candidate hypotheses. Mori et al. [Ref. 100] described an example of this approach. The direct implementation of the multiple hypothesis tracking techniques is infeasible due to the excessive growth of the candidate hypotheses. A practical multiple hypothesis tracking implementation can be obtained by using pruning techniques, which limit the depth of the multiscan association [Ref. 3].

Kanyuck and Singer [Ref. 112] proposed the first modeling track-to-track association technique. Their correlation method simply represents a gating technique.

Two track estimates, from two different systems, are said to be correlated if and only if the difference between all their attributes fall within certain gates or bounds. The gate sizes depend on the system accuracy in terms of the standard deviation of the attribute noise. Singer and Kanyuck [Ref. 113, 114] reconsidered the same problem and developed track-to-track association technique based on a test statistic assuming that the two estimation errors of two different systems are independent. The common test statistic is a weighted difference of estimates. The weights depend on the covariance associated with each estimate. Willner et al. [Ref. 115] addressed the problem of track fusion of two-track estimates, assuming independent estimation errors. Bar-Shalom [Ref. 7, 116] presented the same problems of track-to-track association and track fusion with the assumption that the estimation errors of different systems are correlated (dependent). The results show that the estimation error can be reduced by taking the cross correlation between the two estimates into consideration [Ref. 116, 137, 133].

The track fusion problem with dissimilar sensor accuracies is discussed in several papers [Ref. 118, 119, 133, 143, 148, 149, 150, 151, 152, 153, 154]. The results show that under certain conditions the performance of the fused track may be worse than that of the better quality sensor track. Saha and Chang [Ref. 92, 120, 136] showed that the performance of the fused estimate is marginally better than that of the better quality sensor track when the sensors are dissimilar (with different sensor accuracies). The best performance of the fused estimate occurs when the two sensors are similar. The performance of the fused track is worse than the performance of the better quality estimate when the two sensor noise variances vary widely [Ref. 119, 137]. In this case, it is recommended to adopt the estimate of the better quality sensor, and the fusion of both sensor estimates is not recommended.

In general, the computational cost in generating the optimal solutions for the data association problem is excessive for real-time surveillance systems. Furthermore, they require ideal modeling assumptions and *a priori* knowledge of the signal environment, which is limited in practice. We can remark that the use of an optimum,

complicated association technique under ideal assumptions may not be more desirable than a suboptimal, simple association technique that requires little or no *a priori* information [Ref. 1, 2].

Unlike the algorithmic category, the nonalgorithmic category provides approximate solutions to the problem of data association. Sengupta and Ittis [Ref. 101] developed an analog neural network to emulate the *JPDA*. Their approach is capable of handling six targets and twenty measurements at most. The implementation is difficult due to the heuristic nature of the approach. Brown et al. [Ref. 175] described neural network implementations for the data association algorithms in *MSMT* environment. Major drawbacks to the neural network implementations are that they require a large number of neurons and require training using a very large set of tracks [Ref. 12, 132], [Ref. 163]- [Ref. 165].

Fuzzy systems have been successfully applied to many important application areas, such as medical imaging, robot vision, remote sensing, sonar systems and pattern recognition [Ref. 43, 80, 97, 166]. Fuzzy logic based algorithms have become a powerful technique for multisensor data fusion [Ref. 62, 99, 105, 139, 158, 178]. Fuzzy systems are well-suited to manage uncertainty and to model decision making processes [Ref. 39, 54, 55, 96] and offer the advantage of a clear understanding of their operation because they construct knowledge by rules that resemble human thinking.

In fuzzy system design, users start with some fuzzy rules, which are chosen heuristically based on their experience, and membership functions, which in many cases are chosen subjectively based on an understanding of the problem, and they use the resulting system to tune these rules and membership functions. For the problem of data association in *MSMT* environment, the distributed sensors use their input data (features) to form an opinion, in the form of a fuzzy membership, on the environment [Ref. 57]. The features and known prototype features are fuzzified using the same membership functions. The outputs from the fuzzification are values between 0 and 1 and represent the grades of membership of all data points to all clusters. These outputs are called fuzzy outputs. The fuzzy outputs from the

fuzzification process are processed using fuzzy rules represented as *IF THEN* rules. The defuzzification process converts the fuzzy outputs to non-fuzzy outputs, which are called crisp data. The defuzzified outputs are analyzed and compared with each other or with thresholds to determine the actual clustering (association).

Several recent studies have been devoted to the application of fuzzy techniques to data association. Wide et al. [Ref. 17] developed a fuzzy technique for classification of measurements in different known quality profiles. Hossam et al. [Ref. 11] developed a fuzzy approach for solving the data association problem in target tracking assuming a single sensor. In their approach, the measurement that has the maximum degree of membership is chosen as the true measurement. Smith [Ref. 14, 74, 91] developed a fuzzy logic association approach for track-to-track association in a *MSMT* environment. He utilizes the fuzzy clustering algorithm to determine the grades of membership of all observations for a known number of targets. His approach requires initialization of either the prototype values or the grades of membership. Tummala et al. [Ref. 75, 76, 77, 131] developed a fuzzy track-to-track association algorithm. It is applied to a real scenario of multisensor multi-vessel within the United States Coast Guard Vessel Traffic Services system. In their algorithm, the differences between attributes of two tracks are fuzzified using fuzzy membership functions and compared to that of the fuzzified outputs subject to sensor accuracy limitations. A membership function for each attribute is chosen subjectively according to the corresponding system error. Their algorithm is tested using simulated and real data and is proved to be efficient.

Singh and Bailey [Ref. 58] developed the first fuzzy logic approach for measurement-to-track association in *MSMT* tracking. In their approach, fuzzified position and velocity errors are used by a fuzzy knowledge-base (*IF THEN* rules). The position and velocity errors are fuzzified using triangular membership functions. Then defuzzification and fuzzy set decision are performed to obtain the actual association of observations to tracks. Their approach is applied to the cases of one and two targets. Unfortunately, the extension of their approach to the case of large number of targets

is fairly complex due to the large number of rules required. Furthermore, as the system complexity increases, it becomes difficult to determine the right set of rules and membership functions to describe the system behavior. Although Singh and Bailey [Ref. 58] addressed the critical problem of constructing the optimal membership function for a given distribution of the data, constructing membership functions from statistical data requires the knowledge of the distribution of the data and assumes stationarity of the statistical environment. Furthermore, the optimal membership function in fuzzy system design is constructed by approximating a number of sub-membership functions [Ref. 56, 58, 102, 103]. In general, the fuzzy logic approach to data association provides an approximate solution, and the accuracy of the solution depends on several factors, such as the number of input variables, the number of linguistic variables, the choice of membership function, and the accuracy of the fuzzy rules and statements.

B. DISSERTATION OBJECTIVE

The main objective of this dissertation is to develop fuzzy techniques to solve the problems of measurement-to-track association, track-to-track association, and track fusion in multisensor-multitarget environment with overlapping sensor coverage. The other objectives are to reduce the computational complexity and to achieve performance improvement with little or no prior knowledge.

Data association is the central function of Level 1 processing in the data fusion model. Given measurements (observations) from different distributed sensors, data association is responsible for partitioning these measurements into sets that could have originated from the same targets. In measurement-to-track association, measurements are selected from many sensors to maintain and update the tracks. The key function here is the association of measurements to targets before target state estimates can be made from the measurements. The performance of any tracking algorithm is mainly governed by the performance of the data association technique used. Correct data association enhances the tracking performance and vice versa. If the sensor selects

the right observation to update a target state estimate, then the target will be tracked correctly and the estimated target's position will be close to the true target positions; otherwise, the track will be lost. In track-to-track association, all measured tracks from different sensors are processed in a data fusion center to determine whether or not two tracks represent the same target (distributed data association problem). Track-to-track association combines redundant tracks, provided by different sensors on the same targets, into a unique set of tracks. Track fusion addresses the issue of fusing two or more tracks if it is determined that they represent the same target [Ref. 3, 7, 92, 134, 147]. Fusion of sensor tracks improves track performance if track fusion is done appropriately.

C. ORGANIZATION

The remainder of the dissertation is organized as follows. In Chapter II, we introduce the general model of multisensor data fusion. In Chapter III, we describe the general data association process and survey different techniques of measurement-to-track association, track-to-track association, and track fusion including algorithmic and nonalgorithmic techniques. In Chapter IV, we develop a nearest-neighbor fuzzy measurement-to-track association approach. The performance and the computational complexity of the proposed approach are analyzed and compared to that of conventional fuzzy approaches reported in the literature [Ref. 58]. In Chapter V, we develop a new all-neighbor fuzzy association approach. Its performance is evaluated and compared to that of nearest-neighbor standard filter and perfect data association. The main focus of Chapter V is to demonstrate the feasibility of applying fuzzy logic techniques to all-neighbor association techniques. In Chapter VI, we propose a novel fuzzy track-to-track association and track fusion approach. We also develop fuzzy association techniques based on the fusion of association decisions. A new fuzzy association rule based on the concept of cross-resolution is developed. Applications of the proposed track-to-track association to real data obtained from the United States Coast Guard Vessel Traffic Services system are demonstrated.

Since the primary function of sensor fusion is the detection of targets before any data association can be made, we address the problem of optimum decision fusion rules in multisensor distributed detection systems in Chapter VII. The two major structures for decision fusion: centralized (optimum structure) and decentralized structure, are analyzed. An efficient fuzzy logic (soft) decision approach in multisensor distributed detection systems is proposed. The proposed approach has detection probability improvement over a comparable hard-decision approach. The results characterize the performance trade-off between the centralized, decentralized, and soft decision approaches, allowing us to choose a preferred communication architecture according to the available communication bandwidth. Finally, in Chapter VIII, we present conclusions and suggestions for future research.

There are five appendices in the dissertation. Appendix *A* includes the Kalman filter equations. Appendix *B* presents the derivation of the covariance update equation of the probabilistic data association filter. The derivation of track fusion relationships that minimize the expected mean square error is included in Appendix *C*. Appendix *D* contains the definitions and operations of the fuzzy set theory. Derivation of the fuzzy clustering means algorithm is presented in Appendix *E*.

II. MULTISENSOR DATA FUSION

Data fusion is an important problem in a variety of applications. In a data fusion system, a number of distributed sensors, with different accuracies and characteristics, sense multiple objects in a noisy environment and report all the processed data to a data fusion center. The data fusion center combines (integrates) all the received information from the multiple sensors into a unique set of meaningful information of the sensed objects. Data fusion improves system performance and yields more accurate information if fusion is done appropriately. The data fusion systems may consist of local sensors linked physically to a data fusion center, distributed sensors linked electronically to a data fusion system, and other data, such as data base information and reference data fused in a central processor [Ref. 130]. Applications for multisensor data fusion are widespread in both military and civilian applications. This chapter provides an overview of data fusion, introducing the data fusion model, data fusion applications and taxonomy of multisensor multitarget data fusion [Ref. 1, 2, 5, 9, 130, 182].

A. APPLICATIONS OF MULTISENSOR DATA FUSION

Multisensor data fusion has a wide variety of application areas ranging from military to nonmilitary applications. Historically, data fusion has been devoted to military applications. Nevertheless, several nonmilitary applications in the civilian world have been studied recently. Military applications include remote sensing, ocean surveillance, guidance and control of autonomous vehicles, automated threat and target recognition, air-to-air and surface-to-air defense, and battlefield surveillance. In air-to-air defense and surface-to-air defense applications, the main objectives are to detect, track and identify aircrafts. In these systems, generally called identification friend and foe (*IFF*) [Ref. 138], electromagnetic radiation (such as infrared and radio frequencies) are observed using passive sensors (such as electronic support measures receivers) and active sensors (such as radar) in a surveillance volume to identify

whether the sensed aircraft is a friend or a foe aircraft. A similar nonmilitary application is the identification of an incoming aircraft at civilian airports [Ref. 2]. Nonmilitary applications include automated monitoring of equipment, medical diagnosis, and robotics. Multiple sensor medical data (such as ultrasound, x-ray images and chemical tests) are tested to diagnose the illness of a patient [Ref. 1, 2].

B. MULTISENSOR DATA FUSION MODEL

A functional model for multisensor data fusion is illustrated in Figure 1 [Ref. 36]. It incorporates three basic levels of processing: levels 1, 2, and 3. Level 1 processing consists of positional fusion, which combines locations derived from all sensor data to obtain the most accurate estimate of an entity's position [Ref. 1, 9, 19, 20] and velocity, and identity fusion, which combines data related to the identity of entities (e.g., classification of entities into classes and the identity of an enemy aircraft, ship or emitter) [Ref. 24, 25]. The term entity refers to a target, an emitter, or a platform.

The positional fusion is divided into two subgroups: parametric association and estimation techniques [Ref. 6, 8] (see Figure 2). Parametric association associates (correlate) observations from multiple sensors to individual entities (tracks). That is, multiple targets are observed by multiple sensors, and the association between observations and targets is not known *a priori*. Parametric association is important because an incorrect data association would affect the performance of the target tracking. Given the association of each observation to each target, estimation techniques are then used to combine the data to obtain better estimate of the state vector attributes (such as position and velocity).

Level 2 processing is aimed at situation assessment, a process by which a description of the relationships among all entities is developed. In this level, the outputs from Level 1 processing are analyzed and examined to bring out the essential features of the distributed combat units and weapon systems. Level 3 processing is used for threat assessment. Its purpose is to determine the meaning of the fused data, such as

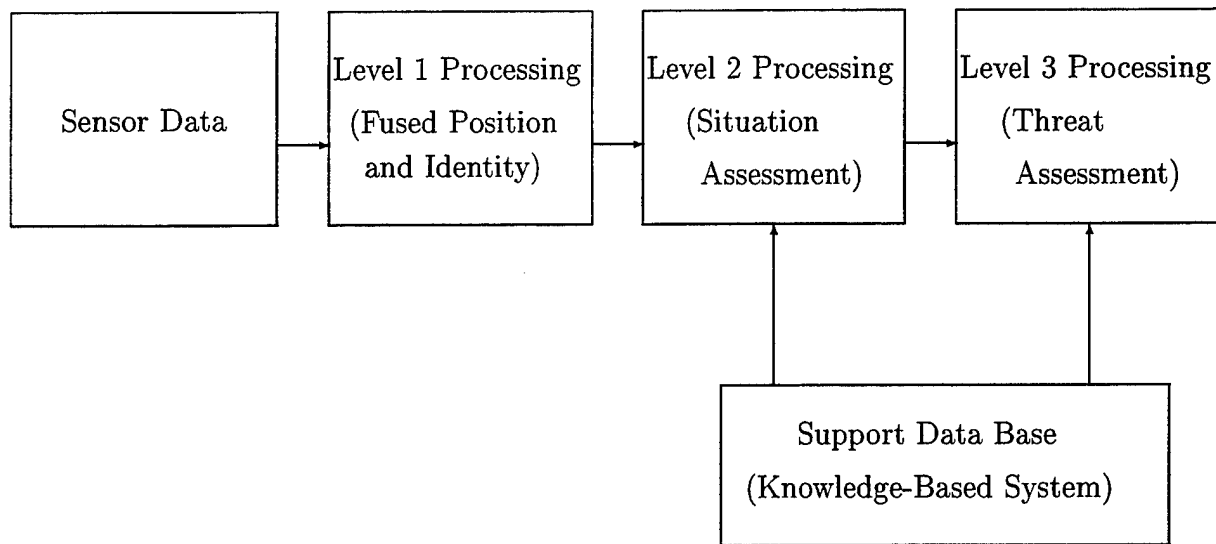


Figure 1. Data Fusion Model

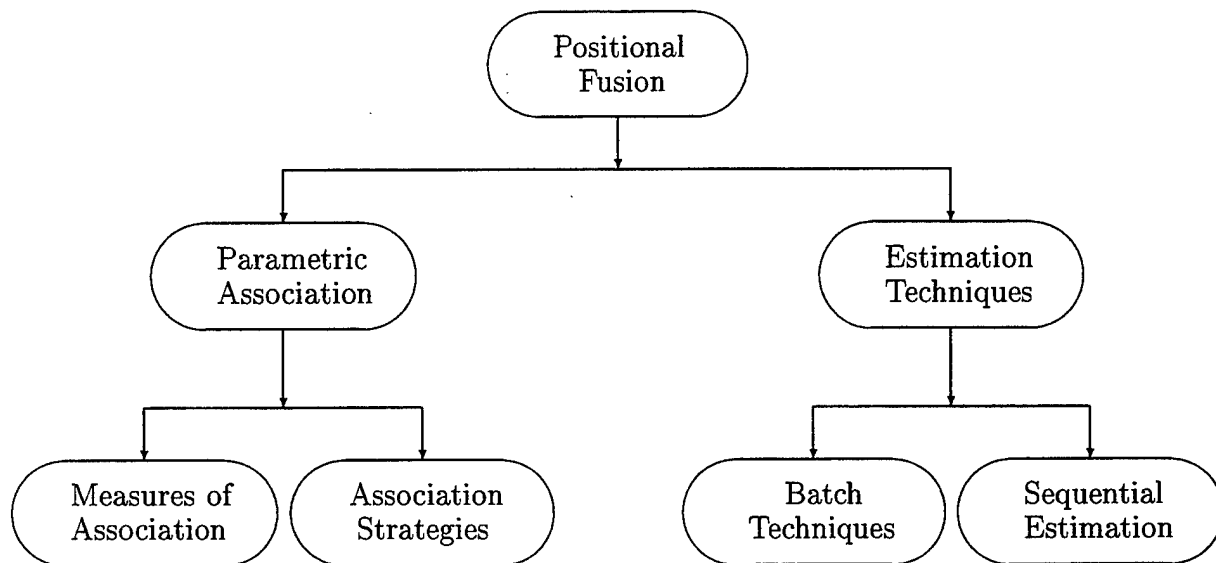


Figure 2. Taxonomy of Positional Fusion Algorithms

an estimate of enemy lethality, expected courses of action, unit compositions and deployment, and an estimate of threat. This level usually employs heuristic techniques similar to those for situation assessment in addition to utilizing the knowledge-based systems or expert systems (support data base). The aim of this dissertation is to develop techniques for data association and sensor fusion in distributed *MSMT* environment, which are part of Level 1 processing.

1. Level 1 Processing in Multisensor Data Fusion

Level 1 processing performs four main functions: (1) data alignment, (2) data association, (3) tracking, and (4) identification [Ref. 1, 2, 6, 130]. Figure 3 illustrates the four basic functions involved in Level 1 processing. The data alignment function transforms sensor data into a common set of coordinates and units. Converting the data received from each sensor to a common coordinate system is necessary to fuse target information from dissimilar sensors (sensors with different accuracies/resolutions). The data association function correlates the sensors data to entities, and the tracking function combines positional data to yield an estimate of the target state vector. The two main techniques used for estimation are batch estimation techniques and sequential estimation techniques. The identification function combines information to determine the identity of entities (classification of targets) [Ref. 24]. We focus on data association techniques in the remainder of the dissertation.

C. BENEFITS OF DATA FUSION

Multisensor data fusion takes advantages of redundancy and diversity present in the data. Consider an example [Ref. 130] in which an aircraft is observed by two different sensors: a pulsed radar and an infrared imaging sensor (see Figure 4). The radar can measure range with high accuracy but measures the direction of the aircraft with low accuracy. On the other hand, the infrared imaging sensor can measure the direction of the aircraft with high accuracy but cannot measure the aircraft's range. If the measured data from both sensors are correctly combined, then the fused sensor data has better accuracy in both range and bearing, i.e., a performance improvement

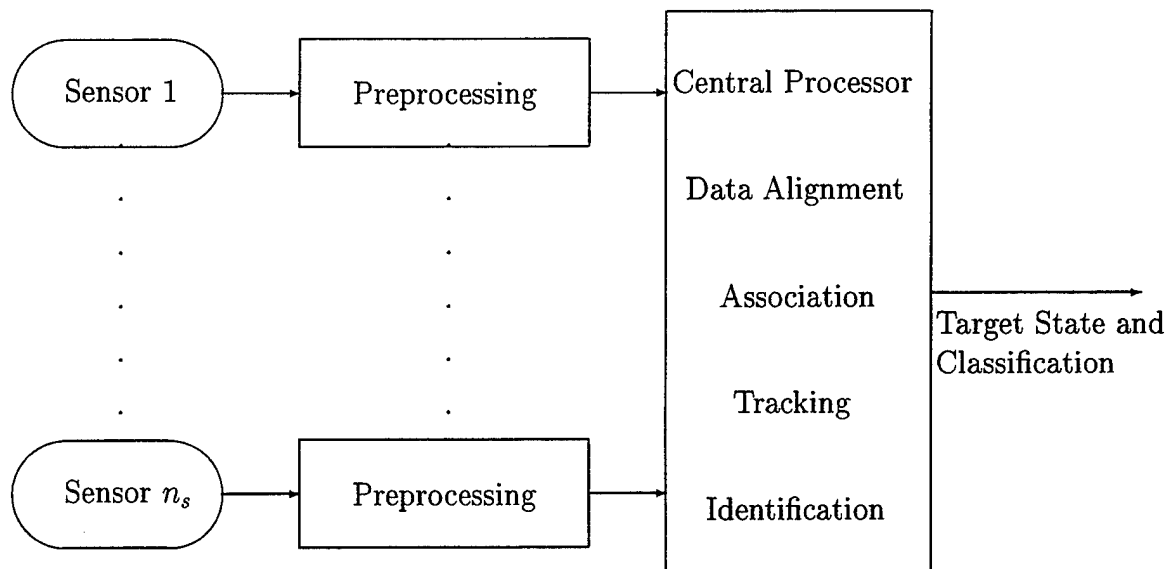


Figure 3. Level 1 Processing

is achieved over either of the two independent sensors.

Practical determination of the advantages of data fusion requires simulated examples (Monte Carlo simulations). Ashraf et al. [Ref. 194] provide a simulated example in which two dissimilar sensors observe a common target. In this example, each sensor output is a decision, $u_i, i = 1, 2$, regarding the presence ($u_i = 1$) or the absence ($u_i = 0$) of the target. The sensor decisions are reported to a data fusion center, which combines them to obtain a global decision (u_0). Since the reported sensor data is binary, two possible fusion rules are the *OR* fusion rule (a target is present if either of the two sensors detects the target) and the *AND* fusion rule (a target is present if and only if both sensors detect the target). Figure 5 compares the receiver operating characteristic (*ROC*), a plot of the detection probability versus the false alarm probability, of the *OR* and the *AND* fusion rules as well as the individual sensor's *ROC*s for the case of exponentially distributed observations. The global performance improvement of the *OR* and the *AND* fusion rules over the individual sensors *ROC*s is obvious.

Hall [Ref. 2] describes the benefits of data fusion and the corresponding ap-

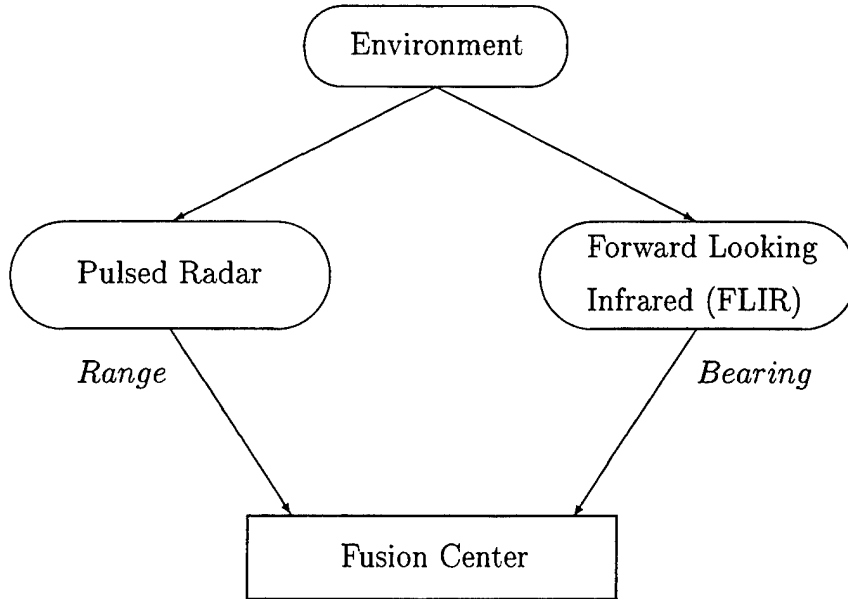


Figure 4. FLIR and Radar Sensor Fusion

plications for both military and nonmilitary applications. The various benefits result in improved operational performance, extended spatial coverage, extended temporal coverage, increased confidence, reduced ambiguity of inferences, improved detection performance, enhanced spatial resolution, improved system operational reliability, and increased dimensionality.

D. MULTISENSOR DATA FUSION ARCHITECTURES

Waltz and Hall [Ref. 1, 130] describe three architectural approaches to data fusion: centralized, decentralized, and hybrid. In the centralized architecture, all sensor observations (raw data) are transmitted to a central processor. The central processor processes all the sensors information and performs Level 1 processing. The sensors do not process the observations. This requires transmission of sensor information without delay which requires a large communication bandwidth and memory.

In the decentralized architecture, the processing is distributed among the sensors and a fusion center. The sensors process the observations and derive local tracks. The fusion center combines the received tracks from the various sensors into a unique

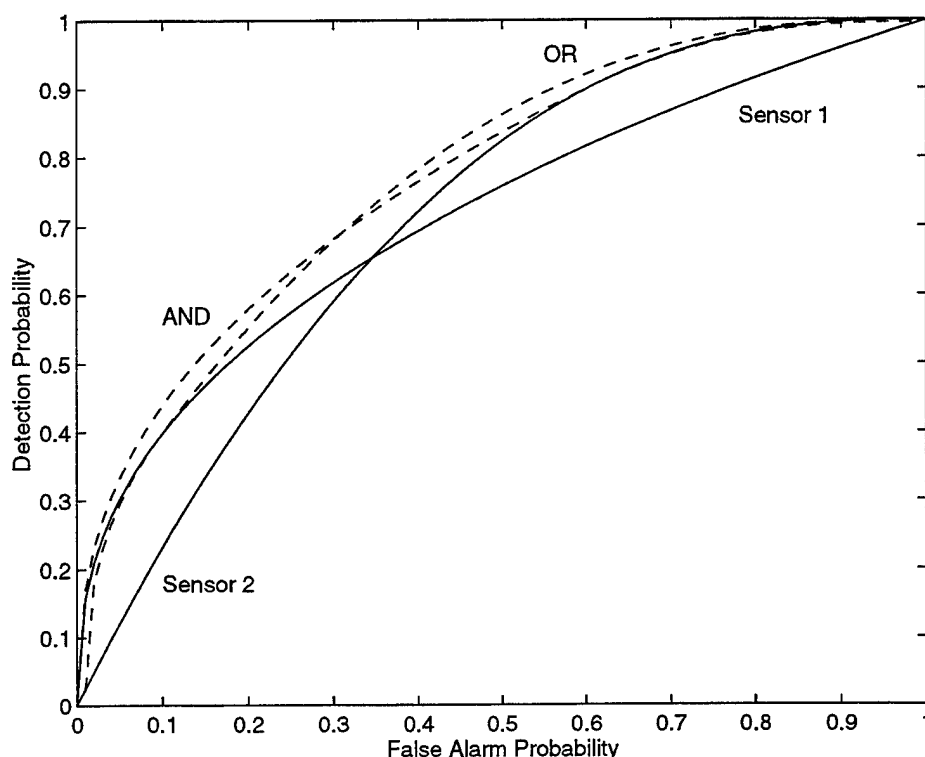


Figure 5. Comparison of *ROC*s of Two Dissimilar Sensors Using *AND* and *OR* Fusion Rules as well as the Individual Sensor *ROC*s

set of tracks. In this case, Level 1 processing is performed on state vectors rather than raw data. Despite performance loss which could result from this architecture, an important practical advantage is the requirement of low-bandwidth data links between the sensors and the central processor [Ref. 59]. Even though the centralized architecture is theoretically the optimum architecture, due to considerations such as communication bandwidth and memory, it is not used in practice [Ref. 50]. The hybrid architecture is a combination of the centralized and the decentralized architectures. The trade-offs among the three architectures are the required communication bandwidth, memory, and computational complexity of the data fusion center. Hall [Ref. 2] presents a detailed description of these trade-offs among these three architectures.

III. TECHNIQUES FOR DATA ASSOCIATION

A. DATA ASSOCIATION PROCESS

A general data association process consists of three main steps: a gating technique, an association metric and an assignment strategy. This is illustrated in Figure 6 [Ref. 2, 3, 180]. The Gating technique eliminates unlikely observation-to-track pairings using *a priori* statistical knowledge. This step is used to reduce the number of combinations of observations-to-track pairs that will be considered for data association. In the second step, we determine a similarity measure between all observations and all tracks of existing targets. In the final step, we solve the problem of assigning observations to tracks.

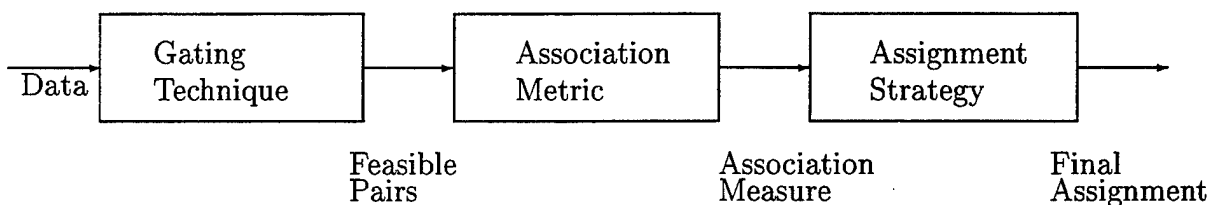


Figure 6. A General Data Association Process

1. Gating Techniques

Given a set of attributes $\{y_i\}$, gates are formed around the predicted target attributes $\{v_j\}$, represented as a function of the state vectors $\{x_j\}$. The target attributes are parameters, such as velocity, position, bearing, and ID number. If some attributes fall within the gate of a track, they may be associated with the corresponding track. All other attributes outside the gate cannot be associated to the target. If a single observation falls within a gate and does not fall within any other track's gate, that observation will be associated to the corresponding track and no further action is needed in the data association process (no conflict situation). If more than one observation fall within a gate or if an observation falls within more than one gate, further processing is needed (conflict situations). Thus the gating techniques reduce the number of computations by providing only feasible pairs of observations and tracks [Ref. 3, 7, 34, 144].

Gating techniques can solve the problem of data association if there are no conflicts. Figure 7 shows an example of three targets and four observations with no conflict. Since only one observation falls within each target's gate, each observation is assigned to the corresponding track. Figure 8 illustrates the same scenario with conflict. As shown in Figure 8, y_1 can be associated to target 1 or target 2, y_2 can be associated to target 2 or target 3, and y_3 can be associated to target 1 or target 3. Observation y_4 cannot be associated to any target since it is outside the gates of all targets.

The simplest gating technique is the rectangular gating which defines a region such that an observation is associated to a track if all the attributes $\{y_k\}$ satisfy the following relation [Ref. 3, 7]:

$$|y_k - \hat{y}_k| = |\tilde{y}_k| \leq G_k \sigma_r, \quad (\text{III.1})$$

where σ_r is the residual standard deviation and is given by:

$$\sigma_r = \sqrt{\sigma^2 + \sigma_p^2}, \quad (\text{III.2})$$

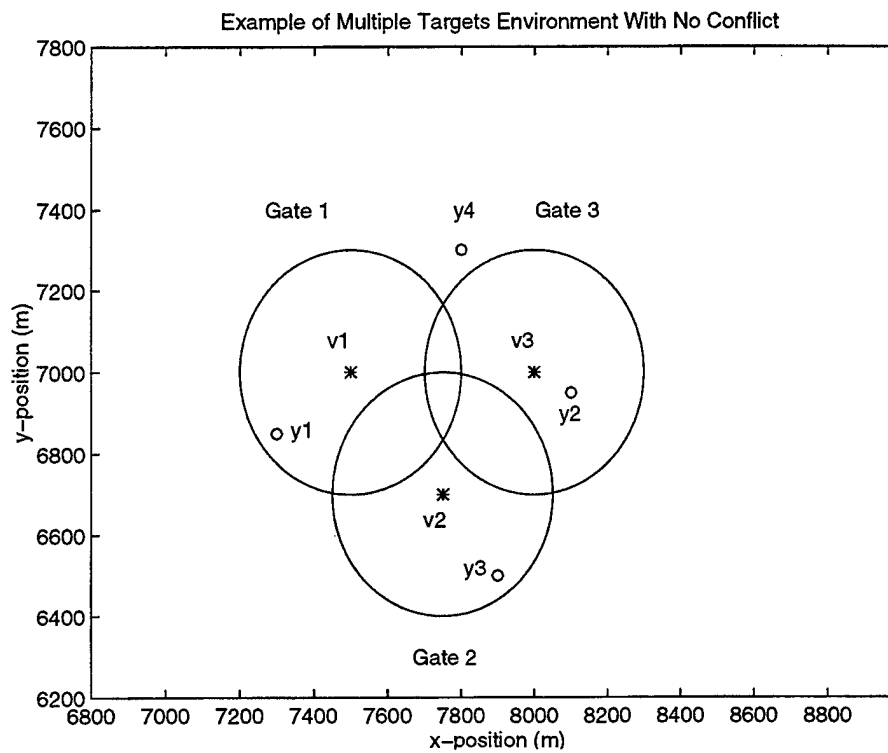


Figure 7. Gating Techniques With No Conflict

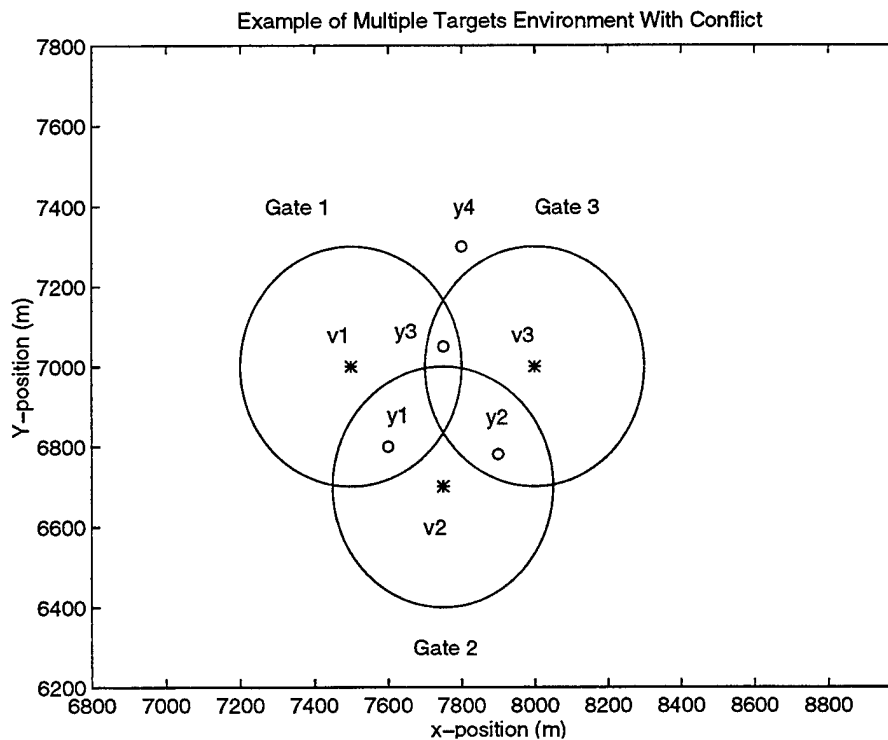


Figure 8. Gating Techniques With Conflict

where σ is the measured standard deviation and σ_p is the standard deviation obtained from the Kalman filter. The basic equations of Kalman filtering are summarized in Appendix A [Ref. 78, 84]. The gating constant G_k depends on the density of the distributed observations, the detection probability and the dimension of the state vector [Ref. 3].

Unlike the rectangular gating techniques, the ellipsoidal gating techniques depend on the norm of the residual vector. An observation \mathbf{y} is said to be within the gate of a given track of predicted attribute vector $\hat{\mathbf{y}}$ if the norm of the residual vector, d^2 , satisfies the following relation:

$$d^2 = (\mathbf{y} - \hat{\mathbf{y}})' S^{-1} (\mathbf{y} - \hat{\mathbf{y}}) \leq G, \quad (\text{III.3})$$

where G is a gating constant and S is the residual covariance matrix. The optimum gating constant G_0 is obtained as a function of the detection probability p_d , the number of attributes, the new target density β_{N_t} , the false target density β_{F_t} , and the residual covariance matrix S [Ref. 3, 171, 172]:

$$G_0 = 2 \ln \left[\frac{p_d}{(1 - p_d)(\beta_{N_t} + \beta_{F_t})(2\pi)^{M/2} \sqrt{|S|}} \right]. \quad (\text{III.4})$$

Another test is to define G based on the chi-square distribution. Since d^2 is the sum of the squares of M independent Gaussian random variables, it has chi-square probability distribution with M degrees of freedom, where M is the total number of attributes (measurements). Let P_G be the value of the probability of a valid observation is within the gate, then

$$P\{d^2 > G\} = 1 - P_G, \quad (\text{III.5})$$

which can be determined using standard chi-square table. The performance of the ellipsoidal gating is noticeably better than the standard rectangular gating techniques [Ref. 3].

2. Association Metrics

For each feasible observation-to-track pair, an association metric, expressed as distance, is computed. The association metric represents the degree of similarity

between two entities. There are four standard criteria that can be used to determine whether or not a metric d is a true metric [Ref. 37, 177]:

$$\begin{aligned} d(a, b) &= d(b, a) \geq 0 && \text{Symmetry,} \\ d(a, b) &\leq d(a, c) + d(b, c) && \text{Triangle inequality,} \\ \text{if } (a, b) &\neq 0, \text{ then } a \neq b, && \text{Distinguishability} \\ \text{if } d(a, b) &= 0, \text{ then } a = b && \text{Indistinguishability.} \end{aligned}$$

There are four types of distance metric [Ref. 177]: correlation coefficients, distance measures, association coefficients, and probabilistic similarity coefficients. The selection of a similarity measure depends on the application.

a. Correlation Coefficient

Given two observation vectors \mathbf{x} and \mathbf{y} of dimension M , the correlation coefficient between the two vectors is defined as [Ref. 85]:

$$r_{xy} = \frac{\sum_{i=1}^M (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^M (x_i - \bar{x})^2 (y_i - \bar{y})^2}}, \quad (\text{III.6})$$

where x_i is the i^{th} attribute, and \bar{x} is the mean of all attributes for observation vector \mathbf{x} ; $-1 \leq r_{xy} \leq 1$. The correlation coefficients can be used for any kind of data. The correlation coefficient describes a shape measurement (geometric distance) and has no obvious meaning because the mean of each vector is summed across all attributes of each vector. This drawback makes the correlation coefficient insensitive to the differences in the magnitude of the attributes used to compute the coefficient. The vectors of high correlation are distributed along a straight line, and the vectors of low correlation are distributed in a wide space. Despite that the correlation coefficient not being a true metric and not satisfying the triangle inequality, it is proven to be effective in a wide variety of applications [Ref. 177].

b. Distance Measure

The distance measure is the simplest and widely used association measure. Unlike the correlation coefficient, the distance measure is a true metric and

sensitive to differences in the magnitude of the attributes. The distance measure has no upper bound and is applicable only to continuous variables. The distance measure has many representations [Ref. 1, 2, 37, 177]; the most common representation is the Euclidean distance

$$d_{xy} = \sqrt{\sum_{i=1}^M (x_i - y_i)^2}, \quad (\text{III.7})$$

which is a special case of the Minkowski distance of order r defined as

$$d_{xy} = \left(\sum_{i=1}^M |x_i - y_i|^r \right)^{1/r}. \quad (\text{III.8})$$

Manhattan distance (city block distance) is another commonly used measure

$$d_{xy} = \sum_{i=1}^M |x_i - y_i|. \quad (\text{III.9})$$

Distance measure is widely used in positional data fusion.

c. Association Coefficient

The association coefficient establishes similarity between vectors of binary variables. An association table is formed between two vectors \mathbf{x} and \mathbf{y} . A typical association table is shown in Table I; 1 refers to the presence of a variable, and 0 refers to its absence. The scalar value a represents the number of features that are present in both \mathbf{x} and \mathbf{y} (value of 1) and b represents the number of features that are present in x but absent in y . The scalar values c and d represent the opposite. An association coefficients can then be defined as [Ref. 1, 85]

$$S_{xy} = \frac{(a + d)}{(a + b + c + d)}. \quad (\text{III.10})$$

The value of S_{xy} ranges from zero to one, where $S_{xy} = 1$ represents complete similarity, and $S_{xy} = 0$ represents complete dissimilarity. There are many definitions of the association coefficients as described in [Ref. 2, 177].

Table I. An Association Table

Vectors of Binary Elements \mathbf{x} / \mathbf{y}	1	0
1	a	b
0	c	d

d. Probabilistic Similarity Coefficient

This type of measure is different from all the previous measures. It is not determined directly from the values of the two vectors. Instead, it depends on *a priori* statistical distribution of the underlying process. This is presented in detail in [Ref. 3, 7, 78, 79] and summarized in Section C.

3. Assignment Strategies

The assignment strategies determine the actual association of the observations to the tracks. This can be done after constructing an association matrix between all the observations and all the tracks. Each element in the association matrix is determined using one of the similarity measures described in the previous section.

The optimal solution is to choose the assignment that minimizes/maximizes the summed total similarity measure [Ref. 3]. Table II shows a typical association matrix for the example given in Figure 8, where the rows represent tracks and the columns represent observations. Table III shows the association matrix after applying the rectangular gating technique. The values in Table III are obtained using the Euclidean distance measure and are chosen arbitrarily to highlight concepts. The optimal solution for this assignment is to choose the assignment that minimizes the summed total distance. In the case of two or three targets and observations, developing the optimal solution can easily be determined by enumeration. In case of a large

Table II. Assignment Matrix for Three Targets and Four Observations

Targets/Observations	y_1	y_2	y_3	y_4
Target 1	d_{11}	d_{12}	d_{13}	d_{14}
Target 2	d_{21}	d_{22}	d_{23}	d_{24}
Target 3	d_{31}	d_{32}	d_{33}	d_{34}

number of targets and observations, finding the optimal solution is time consuming, thus suboptimal solutions are developed.

A possible suboptimal solution is to search the association matrix for the minimum distance measure and make the indicated assignment. This step is repeated until all the tracks are assigned to observations. The suboptimal solution for the example of Table III results in the assignment of observation y_3 to target 1, y_2 to target 3 and y_1 to target 2. The summed total distance in this case is 19. The optimum solution for the same example requires the assignment of observation y_1 to target 1, y_2 to target 2 and y_3 to target 3. The summed total distance in this case is 17.

In the literature, there are two main categories of data association for *MSMT* tracking systems: algorithmic and nonalgorithmic [Ref. 58]. The algorithmic category is based on nearest-neighbor and all-neighbor techniques. The nonalgorithmic category is based on neural network and fuzzy logic techniques.

Table III. Assignment Matrix for Example of Figure 8

Targets/Observations	y_1	y_2	y_3	y_4
Target 1	5	\times	4	\times
Target 2	9	7	\times	\times
Target 3	\times	6	5	\times

B. NEAREST-NEIGHBOR DATA ASSOCIATION TECHNIQUES

In the nearest-neighbor techniques, one observation, at most, can be used to update a given track. The nearest-neighbor techniques use only the nearest-neighbor measurement to update a given track. The nearest-neighbor measurement is the measurement that is closest to the predicted target measurement. In this approach, measurements are assigned to existing tracks in such a way to minimize/maximize an overall similarity measure. Blackman [Ref. 3] provides an excellent description of nearest-neighbor association for *MSMT* tracking. Bar-Shalom [Ref. 120, 137, 146] analyzes the performance of nearest-neighbor techniques under many association events. The similarity measures considered in Section A are classes of suboptimal solutions for the nearest-neighbor data association techniques. An optimum nearest-neighbor data association technique is derived in [Ref. 3, 15, 26] by defining a likelihood function. The likelihood function in a given scan k is defined as a product of the following probability distributions

$$L_k = f_{er}(\tilde{y} | N_u) f_{DT}(N_u | D) f_{TL}(D | N_t) f_0(N_t, F_t), \quad (\text{III.11})$$

where $f_0(N_T, F_t)$ is the probability distribution that there are N_t true targets and F_t false targets, D is track length for a given track, $f_{TL}(D)$ is the probability distribution of track length D for a given track, $f_{DT}(N_u | D)$ is the probability distribution that a given track uses N_u observations that produce N_u detections for track update given that the track length is D , and $f_{er}(\tilde{\mathbf{y}} | N_u)$ is the probability distribution of residual error $\tilde{\mathbf{y}}$ between a given track and an observation within the gate of the track. The conditional probability distributions of Equation III.11 are evaluated based on predefined standard models. For r observations received in a given scan k , the likelihood L_k given by Equation III.11 is evaluated for all possible combinations among all tracks and all observations. The optimum solution to partition the r observations into tracks is the solution that maximizes the likelihood function L_k .

Clearly the evaluation of the maximum likelihood expression in a given scan for all possible observation-to-track combinations is computationally infeasible. Thus the expression of Equation III.11 is never implemented in practice. Instead, suboptimal solutions are developed.

The most common data association technique, based on the maximum likelihood function approach, is the nearest-neighbor standard filter. The nearest-neighbor standard filter chooses the assignment that maximizes the likelihood function of the residual error. For a given track i and an observation j , the likelihood function of the residual error is

$$L_{ij} = \frac{e^{-d_{ij}^2}}{(2\pi)^{M/2} \sqrt{|S_i|}}, \quad (\text{III.12})$$

where d_{ij}^2 is the statistical distance (weighted sum of innovations), given by

$$d_{ij}^2 = \tilde{\mathbf{y}}_{ij}' S_i^{-1} \tilde{\mathbf{y}}_{ij}, \quad (\text{III.13})$$

and S_i is the residual covariance matrix and is defined in Appendix A. The vector $\tilde{\mathbf{y}}_{ij}$ is the residual vector between observation j and track i . The optimum assignment is the one that maximizes the likelihood function L_{ij} between observations and tracks. By taking the first derivative of the logarithmic function of Equation III.13, it is easy to see that maximization of the likelihood function is equivalent to minimizing the

following distance [Ref. 3]:

$$d^2 = d_{ij}^2 + \ell n |S_i|. \quad (\text{III.14})$$

Thus for a given track i the observation that produces the maximum value of the distance measure d^2 is selected to update the track.

C. ALL-NEIGHBOR DATA ASSOCIATION TECHNIQUES

All-neighbor data association techniques update a given track using more than one observation. Bar-Shalom and Fortman [Ref. 7] developed the probabilistic data association (*PDA*) filter and the joint probabilistic data association (*JPDA*) filter in which each measurement is assumed to have originated from either a known target or clutter. The result is that the updated estimate for a given track may contain contributions from more than one observation with some association probabilities [Ref. 159]. In *PDA* and *JPDA*, the predicted target state is updated using a probability weighted sum of innovations (probabilistic score). The *JPDA* method is identical to the *PDA* except that the association probabilities are computed using all measurements and all tracks [Ref. 13, 18, 27, 28, 30, 33]. A detailed derivation of the *PDA* and the *JPDA* can be found in [Ref. 7, 32, 35]. The results are briefly described here.

For a given track j and N_v valid observations, the state estimate at time $k+1$ is given by

$$\hat{\mathbf{x}}_j(k+1 | k+1) = \hat{\mathbf{x}}_j(k+1 | k) + \mathbf{K}_j(k+1) \sum_{i=1}^{N_v} \beta_{ij}(k) \tilde{\mathbf{y}}_i(k+1), \quad i = 1, \dots, c, \quad (\text{III.15})$$

where c is the total number of targets, $\tilde{\mathbf{y}}_i(k+1)$ is the innovation due to observation i at time instant $(k+1)$

$$\tilde{\mathbf{y}}_i(k+1) = \mathbf{y}_i(k+1) - \hat{\mathbf{y}}_j(k+1), \quad (\text{III.16})$$

and $\mathbf{K}(k+1)$ is the standard Kalman filter gain. The state update equation can be written as

$$\hat{\mathbf{x}}_j(k+1 | k+1) = \hat{\mathbf{x}}_j(k+1 | k) + \mathbf{K}_j(k+1) \tilde{\mathbf{y}}_j(k+1), \quad (\text{III.17})$$

where

$$\tilde{\mathbf{y}}_j(k+1) = \sum_{i=1}^{N_v} \beta_{ij}(k+1) \tilde{\mathbf{y}}_i(k+1) \quad (\text{III.18})$$

is the sum of all weighted innovations. The weights are the probabilities that the i^{th} observation comes from a given target j . The update of covariance matrix can also be carried out as (see [Ref. 7] and Appendix B for the derivation):

$$\mathbf{P}(k+1 | k+1) = \beta_0(k+1) \mathbf{P}_1(k+1 | k+1) + \tilde{\mathbf{P}}(k+1), \quad (\text{III.19})$$

where

$$\mathbf{P}_1(k+1 | k+1) = [\mathbf{I} - \mathbf{K}(k+1)\mathbf{H}(k+1)]\mathbf{P}(k+1 | k) \quad (\text{III.20})$$

is the standard covariance update equation, $\beta_0(k)$ is the probability that none of the received observations within the gate of a given track originated from the target, and

$$\tilde{\mathbf{P}}(k+1) = \mathbf{K}(k+1) \left[\sum_{i=1}^{N_v} \beta_{ij}(k+1) \tilde{\mathbf{y}}_i(k+1) \tilde{\mathbf{y}}_i'(k+1) - \tilde{\mathbf{y}}_i(k+1) \tilde{\mathbf{y}}_i'(k+1) \right] \mathbf{K}'(k+1). \quad (\text{III.21})$$

If there is no observation within the gate of a given track, the updated state estimate and covariance matrix will be the previous estimate and the previous covariance matrix, i.e.,

$$\hat{\mathbf{x}}(k+1 | k+1) = \hat{\mathbf{x}}(k+1 | k), \quad (\text{III.22})$$

$$\mathbf{P}(k+1 | k+1) = \mathbf{P}(k+1 | k). \quad (\text{III.23})$$

The calculation of the probability scores is quite complex and computationally intensive; thus optimal solutions are used. The only difference among the optimal solution of *PDA*, and *JPDA* and the suboptimal solutions is the method of calculating the probability scores $\{\beta_{ij}(k)\}$. A large number of suboptimal solutions has been developed in the literature [Ref. 29, 109, 110, 129, 145].

Another version of the *JPDA* is the interacting multiple model joint probabilistic data association. The interacting multiple model *JPDA* is a soft-decision zero back scan association approach (memoryless approach) which combines in a probabilistic score several observations and several dynamic models, in a given scan,

to determine the target state estimate [Ref. 78, 79, 141]. Molnar et al. [Ref. 64] describe an iterative procedure for time-recursive *MSMT* tracking based on an expectation-maximization algorithm. This algorithm depends on the maximum *a posteriori* (*MAP*) estimate of the target state and is proven to be effective compared to the *JPDA* approach at the expense of additional computations.

D. MULTIPLE HYPOTHESIS TRACKING TECHNIQUES

In the data association techniques previously discussed, only the current received observations on each scan are used for the data association process to update the target tracks. This technique is termed single hypothesis tracking. Unlike the single hypothesis tracking techniques, which use hard-decision and zero-backscan association, the multiple hypothesis tracking techniques use hard-decision multiscan association. This means that the association process does not only depend on the current data but also on the previous data [Ref. 3, 7, 155, 173].

Mori et al. [Ref. 100] describe an example of a multiple hypothesis tracking approach. This approach is recognized as the theoretically best approach for the *MSMT* tracking problem under ideal modeling assumptions, yet it requires a considerable amount of computation and memory. Outputs from multiple hypothesis tracking approaches are typically a list of hypotheses that can be ranked by their probability estimates. A number of candidate hypotheses are generated, and the corresponding probability estimates are evaluated after receiving more data. Thus the multiple hypothesis tracking uses later observations to determine prior association. Blackman [Ref. 3] provides more details about the multiple hypothesis tracking techniques. The association probabilities are computed using Bayes' rule

$$P(H_i | \mathbf{y}) = \frac{P(\mathbf{y} | H_i) P(H_i)}{P(\mathbf{y})}, \quad (\text{III.24})$$

where \mathbf{y} is the current measurement data, H_i is a generated hypothesis, $P(H_i)$ is the *a priori* probability of hypothesis H_i before receiving the data \mathbf{y} , $P(\mathbf{y} | H_i)$ is the probability of receiving \mathbf{y} given hypothesis H_i and $P(H_i | \mathbf{y})$ is the *a posteriori*

probability of hypothesis H_i after receiving the data \mathbf{y} . The probability of receiving the data \mathbf{y} , $P(\mathbf{y})$ can be calculated from

$$P(\mathbf{y}) = \sum_i P(\mathbf{y} | H_i) P(H_i). \quad (\text{III.25})$$

The derivation of the association probabilities in three different cases can be found in [Ref. 3, 78, 79]. The results are summarized below.

Case 1: If the observation is a false target

$$P(H_i) = \frac{\beta_{F_i}(1 - p_d)^{N_t}}{C} P(H'_i), \quad (\text{III.26})$$

where β_{F_T} is the density of false targets, p_d is the detection probability, $P(H'_i)$ is the probability that H_i is true before receiving the data, N_T is the total number of existing targets and C is a constant that depends on the scan volume and the densities of the new and false targets.

Case 2: If the observation j belongs to an existing track i

$$P(H_i) = \frac{p_d d_{ij}(1 - p_d)^{N_t}}{C} P(H'_i), \quad (\text{III.27})$$

where d_{ij} is the likelihood function associated with observation j and track i and is given by Equation III.13.

Case 3: If the observation belongs to a new target

$$P(H_i) = \frac{\beta_{N_t}(1 - p_d)^{N_t}}{C} P(H'_i), \quad (\text{III.28})$$

where β_{N_t} is the probability density of new targets.

The central part of the multiple hypothesis tracking is the hypotheses tree representation, which is a representation of the candidate hypotheses after receiving new data [Ref. 2, 3, 64, 78, 79, 94]. Figure 9 illustrates a simple example of the

hypotheses tree given two observations and two scans. Whenever a new observation is received and there is a conflict, a list of hypotheses is generated. Figure 9 uses the notation f_a for false target and N_{tx} for a new target x . In the first scan, when observation $y_1(1)$ is received, two hypotheses are generated; false target and new target A . In the same scan, when observation $y_2(1)$ is received, four new hypotheses are generated. The number of hypotheses grows when a new data set is received in the second scan, and the process continues. The final assignment of observations to tracks is determined according to the maximum value of the association probability among all candidate hypotheses.

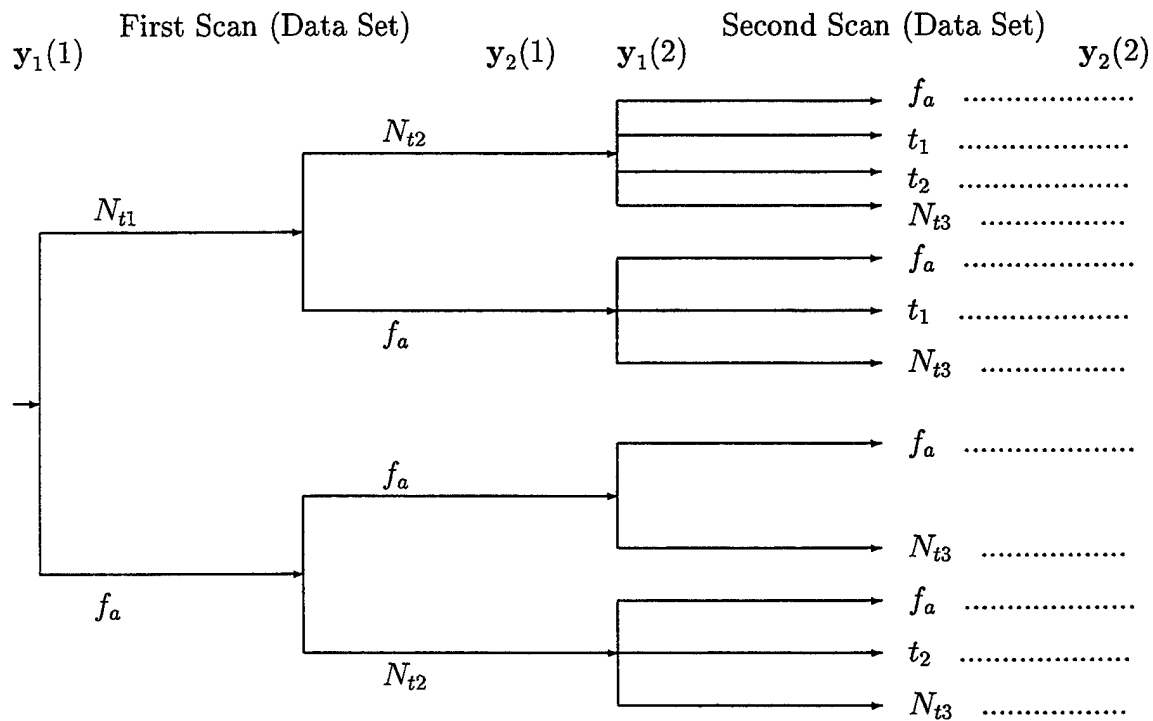


Figure 9. An Example of a Hypotheses Tree Representation

The direct implementation of the multiple hypothesis tracking techniques is infeasible due to the excessive growth of the candidate hypotheses. A practical multiple hypothesis tracking implementation can be obtained by limiting the depth of the multiscan association. The techniques that limit the number of hypothesis are called pruning techniques. The selection of a pruning technique depends on the application. The simplest technique is to remove the hypotheses that have probabilities less than a predefined threshold. Blackman [Ref. 3] describes more details about the pruning techniques.

Feo et al. [Ref. 141] provide a quantitative evaluation of the multiple hypothesis tracking performance and compare its performance with that of nearest-neighbor standard filter . Their results conclude that the multiple hypothesis tracking technique is superior to the nearest-neighbor standard filter as expected at the expense of additional computations.

E. MULTISENSOR-MULTITARGET DATA ASSOCIATION TECHNIQUES

In a *MSMT* environment, there are distributed sensors observing different targets with overlapping coverage. Figure 10 shows a typical example of *MSMT* environment. Each sensor processes its own observations and sends a number of tracks to a data fusion center. The data fusion center processes all the sensor tracks. There are two important questions in such scenario [Ref. 92, 125]. The first question is how to decide whether or not two tracks from different sensors represent the same target (track-to-track association) [Ref. 3, 7, 16, 155]. The second question is how to combine (fuse) the corresponding tracks if it is decided that they represent the same target (track fusion) [Ref. 3, 7, 92, 134, 136]. The use of multiple sensors improves the data association performance and yields more accurate estimates if track fusion is done correctly.

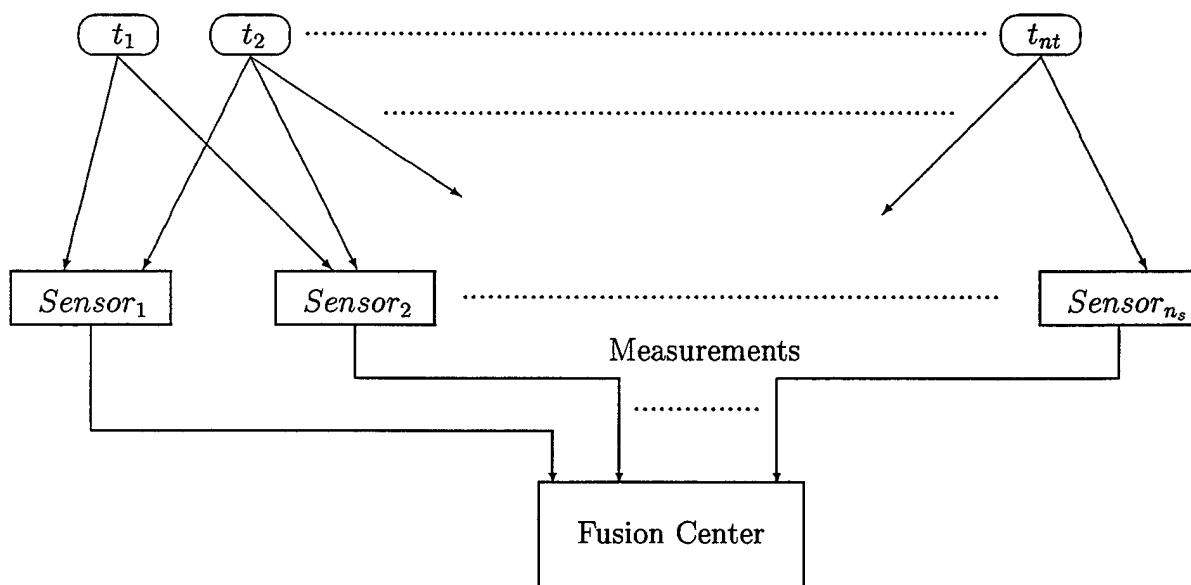


Figure 10. *MSMT* Environment in Overlapping Coverage Scenario

1. Track-to-Track Association Using Gating Techniques

The first track-to-track association approach was implemented using empirical procedures based on the human operator. Due to the limitations of human senses and abilities, especially in a dense target environment, the manual techniques have poor performance. In 1970, the first computer correlation technique has been developed by Kanyuck and Singer [Ref. 112]. This is a gating technique. Given two estimates, \mathbf{x}_{i_k} and \mathbf{x}_{j_k} at time instant k , from two different systems, i and j , the two estimates are said to be correlated (i.e., they represent the same target) if and only if the difference between all their attributes falls within certain gates in at least one of two successive time intervals i.e., if

$$|\mathbf{x}_{i_\ell}(k) - \mathbf{x}_{j_\ell}(k)| \leq \mathbf{G}_\ell(k), \text{ for } \ell = 1, 2, \dots, M, \text{ for } k = 1, \text{ or } 2, \text{ or both,} \quad (\text{III.29})$$

where M is the total number of attributes, k represents the measurement time intervals, and $G_\ell(k)$ is the gating constant at time scan k . The gate sizes depend on the system accuracy in terms of the attribute standard deviations. If we assume that the state estimate contains x and y positions and velocities, then the optimum value of the position gate size is $2\sigma_x(2\sigma_y)$, and the optimum value of the velocity gate size is $4\sigma_{v_x}(4\sigma_{v_y})$. In some examples, this simple track-to-track association technique provides about 15% association improvement over the manual techniques [Ref. 112]. The advantages of the track-to-track association using gating techniques are simplicity and ease of implementation.

2. Track-to-Track Association Using Test Statistic Assuming Independent Estimation Errors

Singer and Kanyuck [Ref. 113, 114] considered the same problem and developed a correlation technique based on a test statistic assuming that the estimation errors of the two different systems are independent. The common test statistic is a weighted difference of estimates, given by:

$$d^2 = (\hat{\mathbf{x}}_i(k | k) - \hat{\mathbf{x}}_j(k | k))'(P_i(k | k) + P_j(k | k))^{-1}(\hat{\mathbf{x}}_i(k | k) - \hat{\mathbf{x}}_j(k | k)), \quad (\text{III.30})$$

where \mathbf{P}_i is the covariance associated with the estimate \mathbf{x}_i (for simplicity, we ignore the time index k). If d^2 is below a certain threshold λ , then the two tracks are the same (i.e., they represent the same target); otherwise, they are different (i.e., they represent different targets). Threshold λ is determined using chi-squared distribution of d^2 assuming Gaussian distributed observations.

3. Track Fusion: Independent Estimation Errors

Willner et al. [Ref. 115] introduced the Kalman filter algorithms for multi-sensor multitarget systems. They use a test statistic to determine whether or not two tracks are the same and solve the problem of track fusion assuming independent estimation errors. There are two different implementations of the fusion algorithms: parallel and sequential [Ref. 93, 95, 115]. In a parallel fuser, the estimates $\hat{\mathbf{x}}_i$ with the corresponding covariances \mathbf{P}_i are applied simultaneously to the fusion center. The fused estimate, which minimizes the expected mean square error, and the corresponding covariance are given by:

$$\mathbf{X}_f = \mathbf{P} \sum_{i=1}^N \mathbf{P}_i^{-1} \hat{\mathbf{x}}_i, \quad (\text{III.31})$$

$$\mathbf{P}^{-1} = \sum_{i=1}^n \mathbf{P}_i^{-1}, \quad (\text{III.32})$$

where N is the total number of the tracks considered in the fusion. In a sequential fuser, the estimates are fused sequentially. The fused estimates of any two tracks $\hat{\mathbf{x}}_i$ and $\hat{\mathbf{x}}_j$ are given by [Ref. 3, 115] (see Appendix C for the derivation):

$$\mathbf{X}_f = \mathbf{P}_j(\mathbf{P}_i + \mathbf{P}_j)^{-1} \hat{\mathbf{x}}_i + \mathbf{P}_i(\mathbf{P}_i + \mathbf{P}_j)^{-1} \hat{\mathbf{x}}_j, \quad (\text{III.33})$$

$$\mathbf{P} = \mathbf{P}_i(\mathbf{P}_i + \mathbf{P}_j)^{-1} \mathbf{P}_j. \quad (\text{III.34})$$

The sequential and the parallel fusers are equivalent in terms of the accuracy of the fused estimate. However the sequential fuser is faster than the parallel fuser since it requires $(N-1)$ inversions of $M \times M$ covariance matrix as opposed to $(2N-1)$ inversions of the same matrix in the parallel fuser.

4. Track-to-Track Association and Track Fusion: Dependent Estimation Errors

Bar-Shalom [Ref. 7, 116] retreated the problems of track-to-track association and track fusion under the assumption that the estimation errors of different systems are correlated. Bar-Shalom mentioned that the measurement noises of two different systems can be assumed to be independent but that is not sufficient to yield the independence of their estimation errors. This is because the same process noise in the dynamic model makes the two estimation errors correlated.

By assuming that the difference between two estimates from different systems i and j is

$$\mathbf{d}_{ij} = \hat{\mathbf{x}}_i - \hat{\mathbf{x}}_j, \quad (\text{III.35})$$

the covariance matrix of the difference of the two estimates is

$$E\{\mathbf{d}_{ij}\mathbf{d}_{ij}'\} = E\{(\hat{\mathbf{x}}_i - \hat{\mathbf{x}}_j)(\hat{\mathbf{x}}_i - \hat{\mathbf{x}}_j)'\}. \quad (\text{III.36})$$

The covariance of the difference can be rewritten as

$$E\{\mathbf{d}_{ij}\mathbf{d}_{ij}'\} = E\{(\hat{\mathbf{x}}_i - \mathbf{x} - (\hat{\mathbf{x}}_j - \mathbf{x}))(\hat{\mathbf{x}}_i - \mathbf{x} - (\hat{\mathbf{x}}_j - \mathbf{x}))'\} = \mathbf{P}_i + \mathbf{P}_j - \mathbf{P}_{ij} - \mathbf{P}_{ji}, \quad (\text{III.37})$$

where \mathbf{P}_{ij} represents the cross-correlation between the two estimates and is given by

$$\mathbf{P}_{ij} = E\{(\hat{\mathbf{x}}_i - \mathbf{x})(\hat{\mathbf{x}}_j - \mathbf{x})'\} = E\{\tilde{\mathbf{x}}_i\tilde{\mathbf{x}}_j'\} = \mathbf{P}_{ji}. \quad (\text{III.38})$$

Taking into consideration the cross-correlation terms, the test statistic given by Equation III.30 will be replaced by

$$d^2 = (\hat{\mathbf{x}}_i - \hat{\mathbf{x}}_j)'(\mathbf{P}_i + \mathbf{P}_j - \mathbf{P}_{ij} - \mathbf{P}_{ji})^{-1}(\hat{\mathbf{x}}_i - \hat{\mathbf{x}}_j). \quad (\text{III.39})$$

In this case, the results of the fused estimate and the corresponding covariance which minimize the *MSE* will be (see [Ref. 116] and Appendix C):

$$\mathbf{X}_f = \hat{\mathbf{x}}_i + (\mathbf{P}_i - \mathbf{P}_{ij})(\mathbf{P}_i + \mathbf{P}_j - \mathbf{P}_{ij} - \mathbf{P}_{ij}')^{-1}(\hat{\mathbf{x}}_j - \hat{\mathbf{x}}_i), \quad (\text{III.40})$$

$$\mathbf{P} = \mathbf{P}_i - (\mathbf{P}_i - \mathbf{P}_{ij})(\mathbf{P}_i + \mathbf{P}_j - \mathbf{P}_{ij} - \mathbf{P}_{ij}')^{-1}(\mathbf{P}_i - \mathbf{P}_{ij}'), \quad (\text{III.41})$$

where \mathbf{P}_{ij} is determined from the following recursive equation:

$$\mathbf{P}_{ij} = (\mathbf{I} - \mathbf{KH}) (\mathbf{F}\mathbf{P}_{ij}\mathbf{F}' + \mathbf{Q}) (\mathbf{I} - \mathbf{KH})', \quad (\text{III.42})$$

where \mathbf{K} is the Kalman filter gain, \mathbf{F} is the state transition matrix, \mathbf{Q} is the plant noise covariance matrix, and \mathbf{H} is the measurement matrix. If correlation between the two estimation errors $\mathbf{P}_{ij} = 0$, then Equation III.40 reduces to Equation III.33 and Equation III.41 reduces to Equation III.34.

Bar-Shalom [Ref. 117] considers the effect of the common process noise on the fused estimates of two different systems. The results show that the cross-correlation between the two estimates reduces the estimation error by about 70% as opposed to 50% when the dependence of the estimation errors is ignored.

The problem of track fusion with dissimilar sensor accuracies is discussed in several papers [Ref. 21, 61, 118, 119, 133, 143, 149, 157]. The results show that under certain conditions the performance of the fused track may be worse than that of the better quality sensor estimate. Numerical [Ref. 118] and theoretical [Ref. 119] results indicate that the performance of the fused estimate is marginally better than that of the better quality sensor estimate when the sensors are dissimilar (with different sensor noise variances). The best performance of the fused estimate occurs when the two sensors are similar. The performance of the fused track is worse than that of the better quality estimate when the sensor noise variances vary widely. In this case, it is recommended that the estimate of the better quality sensor be adopted and the fusion is not performed.

5. Track-to-Track Association of Different Dimensionality Estimates

So far, we considered the association of different tracks with the same number of attributes. Here, the association of tracks with different dimensionality is addressed. In radar to electronic support measures (*ESM*) association [Ref. 126, 127], radar typically provides three attributes while *ESM* being a passive sensor can only provide bearing information. The radar measurements are more accurate than the

ESM measurements. The association problem can be described as follows: given an *ESM* track specified by n *ESM* bearing measurements, it is required to associate the *ESM* track to one of m_r radar tracks. The problem can be described as a multiple hypothesis testing problem:

$$\begin{aligned} H_j &: \text{ESM track associates with the } j^{th} \text{ radar track} \\ H_0 &: \text{ESM track does not associate with a radar track} \end{aligned}$$

The *ESM*-Radar association process was developed by Coleman [Ref. 174] and Trunk and Wilson [Ref. 10]. Coleman [Ref. 174] presents a Bayesian multiple hypothesis test, which determines the *a posteriori* association probability of an *ESM* track to each radar track. The hypothesis with the largest *a posteriori* probability is chosen. By assuming that the *ESM* measurement errors are independent and Gaussian distributed with zero mean and variance σ^2 , the hypothesis with minimum d_j is chosen [Ref. 174], where

$$d_j = \sum_{i=1}^n [\theta_e(t_i) - \theta_j(t_i)]^2 / \sigma^2, \quad (\text{III.43})$$

$\theta_e(t_i)$ is the given measurements of *ESM* sampled at times t_i , n is the total number of *ESM* measurements, and $\theta_j(t_i)$ is the estimated radar bearing of radar track j at the same time t_i . Since the *ESM* measurements are assumed to have Gaussian distribution, d_j has a chi-square density function with n degrees of freedom. Thus the *a posteriori* probability is

$$P_j = P \{z \geq d_j\}, \quad (\text{III.44})$$

where z is a $\chi^2(n)$. The association process chooses the hypothesis that has maximum *a posteriori* probability P_{max} . If P_{max} is less than a threshold T , then hypothesis H_0 is selected. The threshold value depends on the rejection rate.

Trunk and Wilson [Ref. 10] developed a solution for the problem of *ESM*-Radar association based on multi-threshold decision making. Their association process has better performance than that of the single threshold association described by Coleman [Ref. 174].

In general, optimal solutions for data association are not computationally feasible for real-time surveillance systems. Furthermore, the assumptions about *a priori* knowledge of the signal environment limit their usefulness in practice. We can conclude that the use of an optimum, complicated association technique under ideal assumptions may be not better than suboptimal, simple association technique that requires little *a priori* information.

Unlike the algorithmic category, the nonalgorithmic category provides approximate solutions to the problem of data association. Sengupta and Iltis [Ref. 101] developed an analog neural network to emulate the *JPDA*. Their approach is capable of handling six targets and twenty measurements at most. The implementation is difficult due to the heuristic nature of their approach. Brown et al. [Ref. 175] described neural network implementations for data association in *MSMT* environment. A major drawback to the neural network implementations is the need for an unreasonable number of neurons.

F. FUZZY METHODS FOR MULTISENSOR DATA FUSION

Fuzzy systems are well-suited to manage uncertainty and to model decision making processes [Ref. 39, 54, 55, 96]. Fuzzy systems offer the advantage of a clear understanding of their operation because they construct knowledge by rules that resemble human thinking. They can handle numerical data and linguistic information (knowledge), both of which can be transformed into a form of *IF THEN* rules. Fuzzy systems have been proven to be successful in many important application areas, such as medical imaging, robot vision, remote sensing, sonar systems and pattern recognition [Ref. 23, 38, 43, 80, 97, 166] and are becoming a choice technique for multisensor data fusion [Ref. 62, 99, 105, 139, 158, 178]. The distributed sensors use their input data to form local decisions, in the form of fuzzy membership values on the environment; then the local decisions are combined in a data fusion processor to reach a global decision. The basics of fuzzy sets and fuzzy membership functions

are presented in Appendix D.

1. Clustering Techniques

The purpose of any clustering technique is to partition given data into groups or clusters having some common similarity measure. The clusters can be used in classification of the underlying entities. The basic steps involved in any clustering technique are feature selection, similarity measure, clustering, and validation [Ref. 2, 81]. The selection of features depends on the underlying environment. The features can be the measurements themselves. They can be kinematic attributes, such as position, velocity, and bearing, or non kinematic attributes such as shape size and ID number. The features are extracted from the received measurements from all distributed sensors. The similarity measure represents the similarity between the entities based on the selected features. Several types of similarity measures are described in Subsection B.2 of this chapter. The similarity measure must be calculated among all combinations of the entities. The next step is to use a cluster technique to partition the data into entities and then use a validation criterion to express the quality of clustering. Many clustering algorithms have been reported in the literature [Ref. 87]- [Ref. 90], [Ref. 169, 170]. We will describe the Euclidean clustering algorithm to illustrate the concept of clustering. We apply Euclidean clustering to five data points with x and y positions as attributes; the error resolutions of x and y positions are $\Delta(x)$ and $\Delta(y)$. The minimum and maximum number of clusters, c_{min} and c_{max} , are assumed to be two and three, respectively. The cluster radius $\Delta(x, y)$ is defined as [Ref. 14, 74, 91]:

$$\Delta(x, y) = \{[\Delta(x)^2 + \Delta(y)^2]\}^{0.5}. \quad (\text{III.45})$$

The steps of Euclidean clustering are:

1. Start with c_{min} number of clusters with a radius of $\Delta/10$. As shown in Figure 11, the 5 data points cannot be covered with two clusters.
2. Increase the number of clusters by 1 and repeat. Figure 12 shows that the data points cannot be covered with three clusters and a cluster radius of $\Delta/10$.

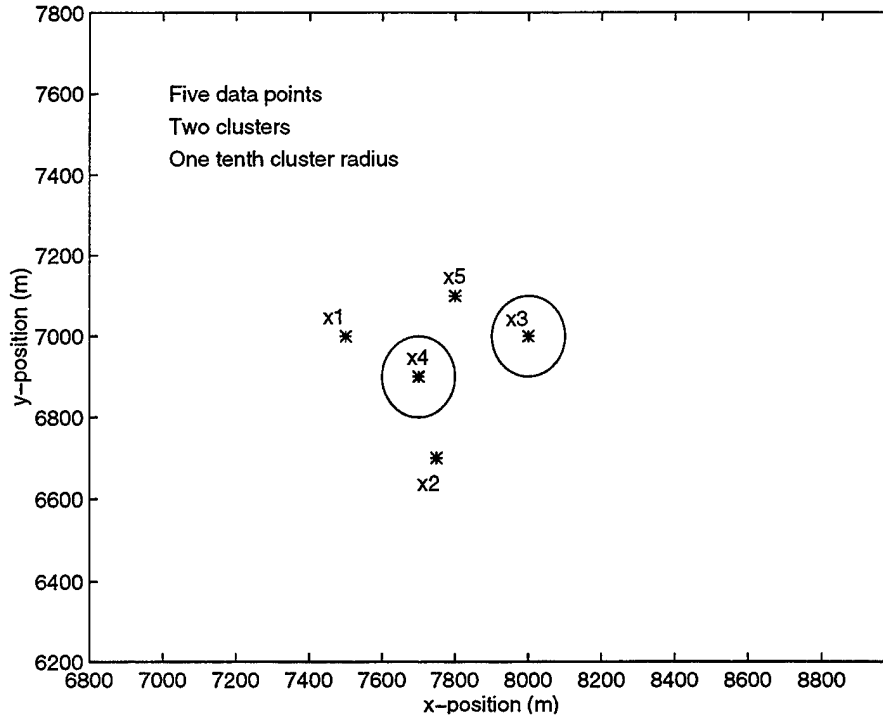


Figure 11. Euclidean Clustering: Step 1

3. Increase the cluster radius to $2\Delta/10$ and repeat if we reach the maximum number of clusters, c_{max} , without covering all the data. Figure 13 shows the results of this step.

4. Repeat steps 2 and 3 until all the data points are covered. As shown in Figure 14, all data points are covered using three clusters with cluster radius $2\Delta/10$.

2. Fuzzy Clustering Techniques

Conventional clustering is hard clustering whereas fuzzy clustering is soft clustering. In fuzzy clustering, each data point can be associated with more than one cluster with some degree of membership. The membership degrees are determined in a way to minimize or maximize a function. The concept of fuzzy clustering is illustrated in Figure 15. As shown in Figure 15, the features are extracted from the received data. The extracted features and known prototype features are fuzzified using membership functions. The outputs from the fuzzification are values between

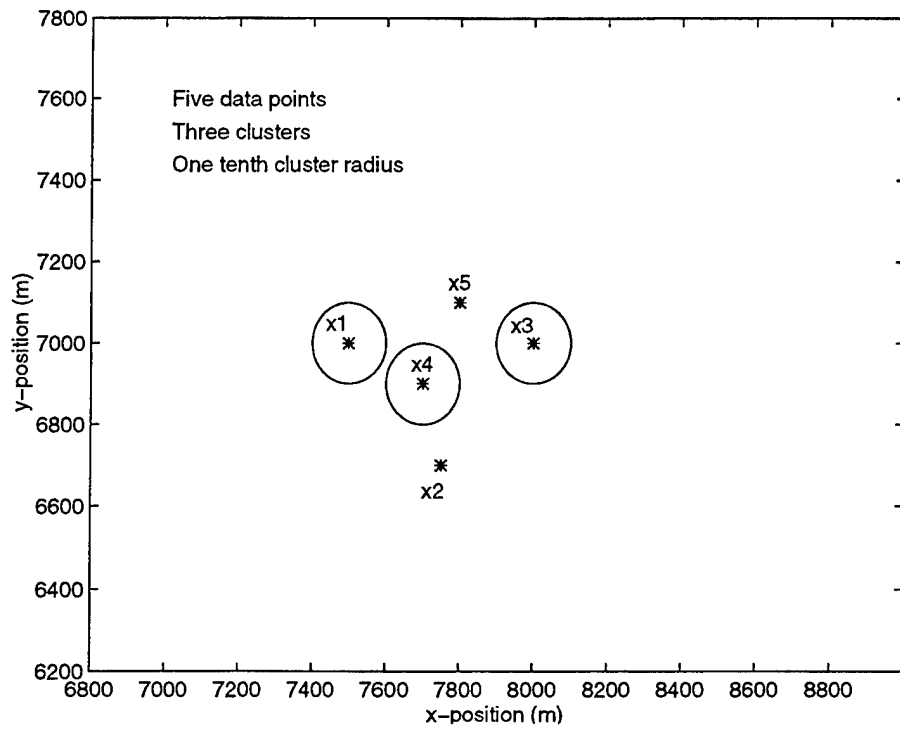


Figure 12. Euclidean Clustering: Step 2

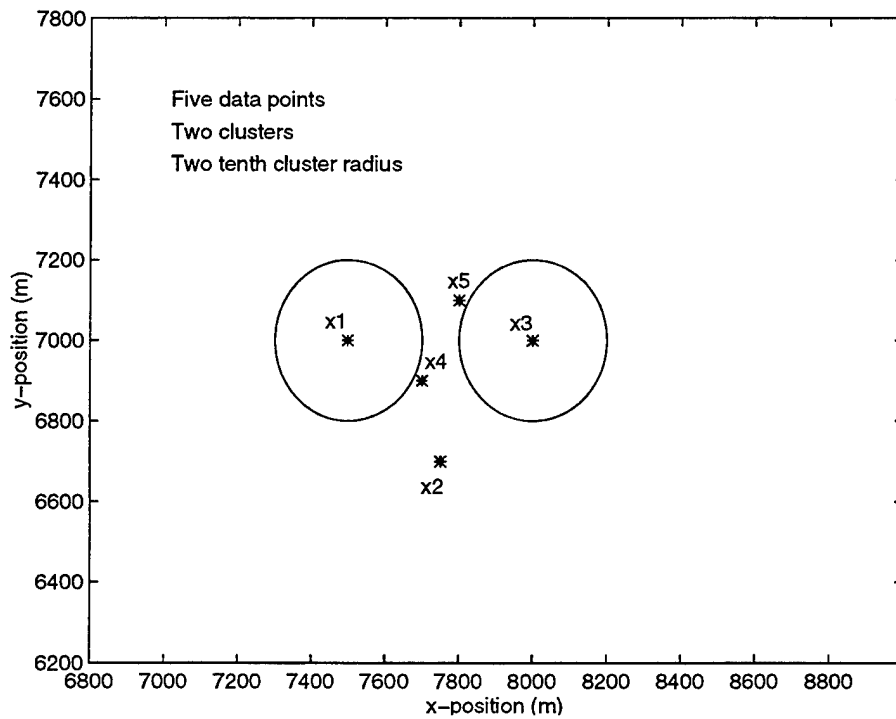


Figure 13. Euclidean Clustering: Step 3

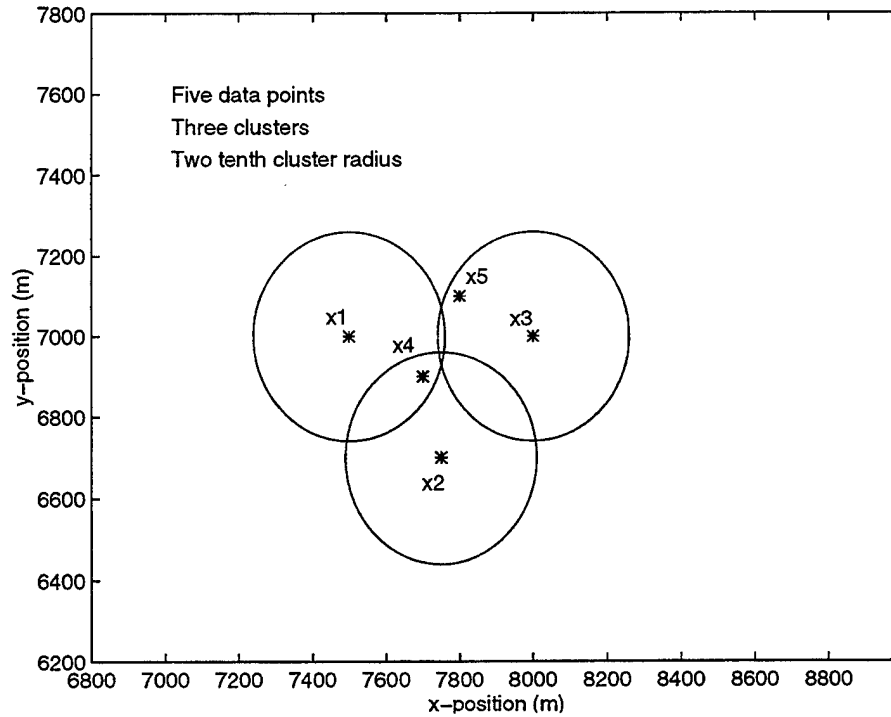


Figure 14. Euclidean Clustering: Step 4

0 and 1 and represent the grades of membership of all data points to all clusters. These fuzzy outputs are processed using fuzzy *IF THEN* rules. The defuzzification process converts the fuzzy outputs to non-fuzzy outputs or crisp data. The defuzzified outputs are analyzed and compared with each other or with thresholds to determine the actual clustering. The two main methods for defuzzification are presented in Appendix D.

There are two types of clustering: in supervised clustering, the number of clusters is unknown; in unsupervised clustering, the number of clusters is known. In unsupervised clustering, the clustering procedures are repeated for all feasible number of clusters until a satisfactory number of clusters that minimize/maximize a pre-defined partition measure is found. The partition measures are chosen heuristically. The process involved in the determination of the optimum number of clusters is called fuzzy validity. There are many partition measures developed in the literature, such as partition exponent [Ref. 107], partition entropy [Ref. 168], partition difference [Ref.

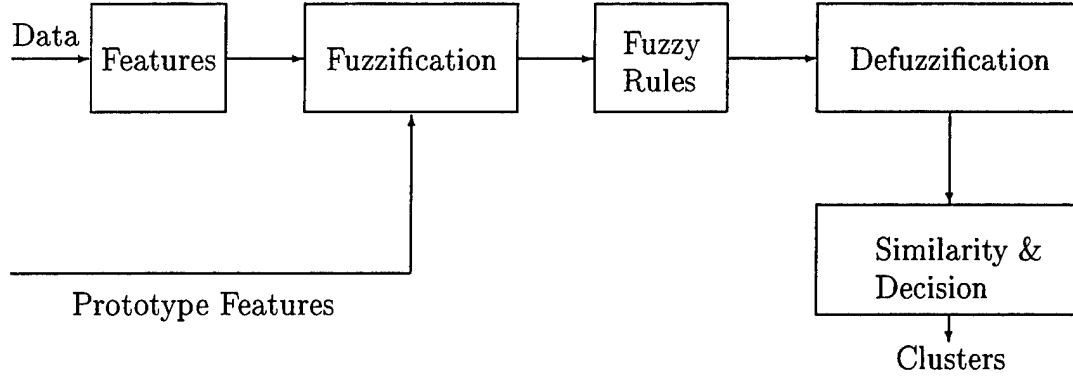


Figure 15. General Structure of Fuzzy Clustering

166] and partition coefficient [Ref. 43]. For example, the partition coefficient is defined as

$$F(\tilde{U}, c) = \sum_{k=1}^c \frac{\mu_{ik}^2}{n}, \quad (\text{III.46})$$

where $\tilde{U} \in M_{fc}$ is a fuzzy c -partition of n data points, c is the number of clusters and μ_{ik} is the degree of membership between measurements i and k . The optimum number of clusters, c_{opt} , is the value that maximizes the partition coefficient among all possible solutions, i.e., choose the number of clusters subject to

$$\max_c \{ \max_{\tilde{U} \in \Omega} \{ F(\tilde{U}, c) \} \}, \quad (\text{III.47})$$

where Ω_c is the set of all optimal solutions for a given c .

Recently, fuzzy clustering has been applied to data association and target identification. Wide et al. [Ref. 17] developed a fuzzy technique for classification of measurements in different known quality profiles. In their approach, the quality profiles and the sensor measurements are fuzzified using arbitrary (triangular) membership functions. The resulting fuzzy measurements and fuzzy profiles are compared

to choose the most representative quality profile for each measurement. Hossam et al. [Ref. 11] developed a fuzzy approach for solving the data association problem in target tracking. Their approach selects the true target measurement from many received measurements for a single target. A fuzzy membership function is assigned to each attribute of the measurement vector. The resulting fuzzy measurements are then defuzzified such that the measurement with the maximum degree of membership is chosen as the true measurement. Smith [Ref. 14, 74, 91] developed a fuzzy logic association approach for measurement-to-track association in *MSMT* environment. He utilizes the fuzzy clustering algorithm to determine the grades of membership of all observations to a known number of target tracks by defining an array of cluster centers with elements

$$c_{ij} = \frac{\|v_i - v_j\|}{\max(\sigma_i, \sigma_j)}, \quad (\text{III.48})$$

where

$$\sigma_k = \sqrt{\sum_{i=1}^n \mu_{ik}^m (x_i - \bar{x}_k)^2 / \sum_{i=1}^n \mu_{ik}^m}, \quad (\text{III.49})$$

$$\bar{x}_k = \frac{\sum_{i=1}^n \mu_{ik}^m x_i}{\sum_{i=1}^n \mu_{ik}^m} \quad (\text{III.50})$$

are the fuzzy standard deviation and fuzzy mean, respectively. Two clusters i and j are merged into one if their cluster centers $c_{ij} < \lambda$, where the threshold λ is determined according to the distribution of the data. For example in case of Gaussian distributed observations, most of the data points fall within three standard deviations of the mean value; thus a suitable value of the threshold is $\lambda = 3$.

Singh and Bailey [Ref. 58] developed a fuzzy logic approach for the data association of observations to tracks. Their approach can be applied to solve data association problems in *MSMT* tracking. The distance measure has not been used in the usual manner, but the distance measures are fuzzified for use by the fuzzy knowledge-base (*IF THEN* rules). Their approach is applied in case of one and two targets with two attributes, position and velocity. The position and velocity errors are fuzzified using triangular membership functions. Defuzzification using centroid method (see Appendix D), and fuzzy set decision are performed to obtain the actual

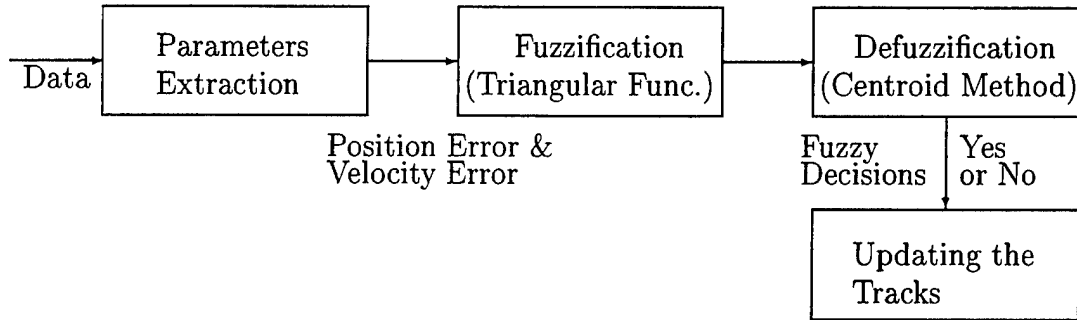


Figure 16. Example of Fuzzy Measurement-to-Track Association Approach

association of observations to tracks. Figure 16 shows the basic steps involved in this approach. The major advantage of this approach is its ability to handle different types of information. Unfortunately, the extension of their approach to the case of more than three or four targets is computationally infeasible due to the large number of rules.

Tummala et al. [Ref. 75, 76, 77, 131] developed an algorithm to solve the problem of track-to-track association using field recording multisensor multi-vessel data. In their algorithm, the differences between attributes of two tracks are fuzzified and compared to the fuzzified outputs of the sensor accuracy parameters (see Figure 17). The two tracks are declared to belong to the same vessel if all fuzzy attribute differences exceed the fuzzy sensor accuracy limits. The membership function for each attribute is chosen heuristically according to the nature of the corresponding system error. Their algorithm can easily be extended for any number of attributes. Their algorithm is tested using simulated and real data and is proved to be efficient.

The general data association process, including gating techniques, association metric, and assignment strategy, has been described in this chapter. A survey of dif-

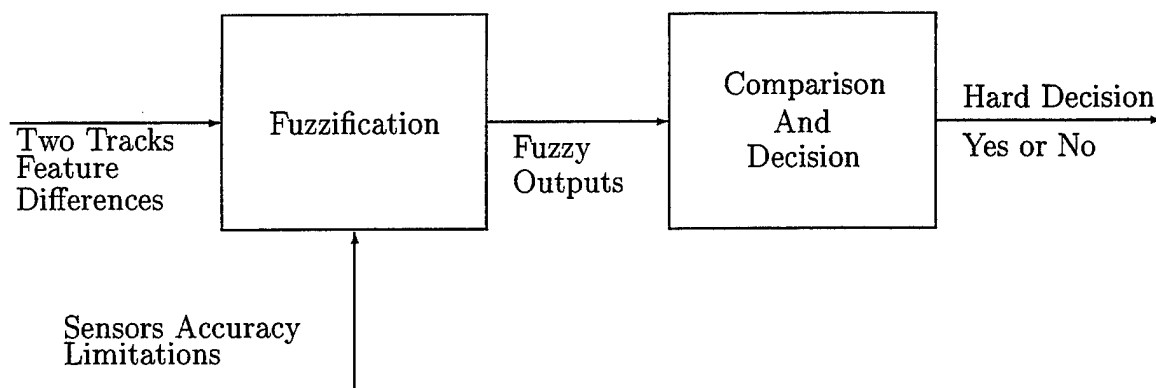


Figure 17. Example of Fuzzy Track-to-Track Association Approach

ferent techniques of measurement-to-track association, track-to-track association, and track fusion including algorithmic and nonalgorithmic techniques has been provided. Fuzzy methods for multisensor data fusion are highlighted. The general structure of fuzzy clustering and its applications to measurement-to-track association and track-to-track association are described.

IV. AN EFFICIENT NEAREST-NEIGHBOR FUZZY MEASUREMENT-TO-TRACK ASSOCIATION APPROACH

A fuzzy rule approach to measurement-to-track association in multisensor-multitarget environment is fairly complex. Furthermore, a fuzzy approach provides an approximate solution, and the results depend on several factors, such as the number of input variables, the number of linguistic variables, the membership functions, and the accuracy of the rules.

Singh and Bailey [Ref. 58] developed the first fuzzy logic approach to the data association problem, and their approach can be applied to solve data association problems, in *MSMT* tracking. In their approach, the distance measure has not been used in the usual manner in the sense that the distance measures are fuzzified for use by the fuzzy knowledge-base (*IF THEN* rules). The major advantage of their approach is its ability to handle different types of information. Although Singh and Bailey [Ref. 58] addressed the critical problem of constructing the optimal membership function for a given distribution of the data, the optimal membership functions are constructed using approximate methods [Ref. 56, 102, 103]. Unfortunately, the extension of their approach to the case of more than three or four targets is computationally infeasible due to the large number of rules.

In this chapter, a nearest-neighbor fuzzy logic data association approach for multisensor-multitarget tracking systems is proposed, based on the fuzzy clustering means algorithm [Ref. 43, 44, 80]. The proposed approach is applied to a two and a four-dimensional multisensor-multitarget tracking system using Monte Carlo simulations. Fuzzy system performance evaluation is presented to demonstrate the effectiveness of the new approach. The computational complexity of this approach is also analyzed and compared to that of conventional fuzzy logic data association methods. It is shown that considerable improvement in terms of computational complexity and performance is achieved.

A. PROBLEM FORMULATION

A significant problem in *MSMT* tracking systems is measurement-to-track association [Ref. 1]- [Ref. 4], [Ref. 7]. A number of approaches have been proposed in the literature to solve this problem ranging from suboptimal, simple, approaches to complex, optimal, approaches [Ref. 10, 29, 92, 93, 95, 109]. The computational cost in generating the optimal solutions to the data association problem is usually excessive when the number of targets and the number of measurements are large. Thus the optimal solutions are not computationally feasible for real-time surveillance systems. Therefore, suboptimal, but computationally feasible, solutions are developed.

Fuzzy techniques are well suited to model decision making processes [Ref. 62, 96, 128, 179]. Although fuzzy systems have several advantages including simplicity and ease in design when the number of rules is small, they are associated with a critical problem. As the system complexity increases, the number of rules increases considerably and it becomes difficult to determine the right set of rules and membership functions to describe the system behavior. As a consequence, the application of fuzzy approaches to solve the problem of measurement-to-track association in *MSMT* tracking systems is complicated in a dense target environment. As an example, if we use conventional fuzzy logic measurement-to-track association techniques [Ref. 58] to solve the problem of associating 6 measurements with 6 tracks using only two input variables (position and speed errors) and 5 linguistic variables (Very Low, Low, Medium, High, Very High), the required number of *IF THEN* rules is $(5 \times 6)^2=900$. Thus the extension of conventional fuzzy logic systems to the case of more than three or four targets increases the computational complexity. Furthermore, the solution of the conventional fuzzy logic approach to the data association problem yields an approximate solution, and the accuracy depends on several factors such as the number of input variables, the number of linguistic variables, the choice of the membership function, and the accuracy of the fuzzy rules and statements.

In this chapter, an efficient nearest-neighbor fuzzy logic measurement-to-track association approach for *MSMT* tracking systems is proposed. The proposed ap-

proach is developed based on the fuzzy clustering means algorithm (*FCM*) [Ref. 43, 80]. The main idea is to determine a partition matrix whose elements represent the degrees of membership of the data in the fuzzy clusters. This approach differs from many fuzzy logic data association algorithms [Ref. 11, 58, 97, 98, 99], which consist of four basic elements: 1) fuzzification of crisp data into fuzzy variables, 2) fuzzy knowledge base containing *IF THEN* rules and fuzzy statements, 3) fuzzy inference which emulates human decision making processes to generate output fuzzy variables, and 4) defuzzification of fuzzy variables into non-fuzzy variables (crisp data). The proposed approach performs data association based on the partition matrix of data (measurements) in fuzzy clusters (tracks). The complexity of the proposed approach increases linearly with the number of observations and it can easily be applied to a dense target environment. Also, its performance is satisfactory in case of large number of observations and targets. Three examples are presented to demonstrate the simplicity and efficiency of the proposed data association approach in a multisensor-multitarget tracking system.

The remainder of this chapter is organized as follows. The problem of constructing the membership functions from statistical data is addressed in Section B. The fuzzy clustering means algorithm is introduced in Section C. The problem formulation and the proposed fuzzy logic data association approach are presented in Section D. Performance evaluation and results using Monte Carlo simulations are reported in Section E. A comparison with other fuzzy logic data association approaches based on the results described in [Ref. 58] is also presented in Section E. A discussion of the computational complexity is presented in Section F.

B. CONSTRUCTING FUZZY MEMBERSHIP FUNCTIONS

In fuzzy system design, we start with a set of fuzzy rules, which in general are chosen heuristically based on their experience, and membership functions, which in many cases are chosen subjectively based on understanding the problem, and they use the developed system to tune these rules and membership functions. Starting

with a good set of rules and membership functions followed by proper tuning is not an easy task and it can be very time consuming for a reasonably complex system. The determination of the membership function is the most important step in the fuzzy system design. Since the inputs of any tracking system are statistical data, the determination of the membership functions based on statistical data should be addressed [Ref. 58]. A criterion for constructing membership functions using the statistics of the data is proposed in [Ref. 56]. The criterion is obtained using infinite dimensional optimization theory. The result is shown in the following [Ref. 56]:

Theorem: For a given probability density function of the data ($p(x)$), the optimal membership function $\mu(x)$ is given by [Ref. 56]

$$\mu(x) = \begin{cases} \lambda p(x) & \text{if } \lambda p(x) < 1 \\ 1 & \text{if } \lambda p(x) \geq 1, \end{cases} \quad (\text{IV.1})$$

where λ is determined from the solution of

$$\lambda \int_{\lambda p(x) < 1} p^2(\eta) d\eta + \int_{\lambda p(x) \geq 1} p(\eta) d\eta - c_\ell = 0, \quad (\text{IV.2})$$

and c_ℓ is a confidence level of the statistical data.

Constructing membership functions from statistical data requires an analytic expression for the statistical distribution of the data (*pdf*) and assumes stationarity of the statistical environment. Furthermore, the optimal membership function in fuzzy systems design is constructed by approximating a number of closely submembership functions. Singh and Balley [Ref. 58] applied these results to approximate the optimal membership function for a Gaussian distribution, which yields a trapezoidal membership function. In the proposed approach, the membership function is determined from the data using the fuzzy clustering means algorithm. The method is easy to implement and reasonably robust as will be illustrated in the following section.

C. FUZZY CLUSTERING MEANS ALGORITHM

The most widely used clustering algorithm is the fuzzy clustering means (*FCM*) algorithm developed by J. Bezdek [Ref. 43, 44, 80]. This section introduces the *FCM* algorithm which will be used for measurements-to-tracks association (correlation). The goal of any fuzzy clustering algorithm is to partition the data into a number of clusters (groups) [Ref. 40, 45, 90, 106] producing a degree (grade) of membership for each data point in each cluster. Unlike conventional clustering, which involves a partitioning of objects into disjoint clusters, fuzzy clustering allows a data point x to have a partial degree of membership in more than one set [Ref. 14, 108, 111]. In this way, given a set of objects X , a fuzzy set A is defined as

$$A = \{(x, \mu_A(x)) \mid x \in X\}, \quad (\text{IV.3})$$

where $\mu_A(x) \in [0, 1]$ is the degree of membership function of the data point x in the fuzzy set A . Given a number of data points, it is required to group (cluster) the data into clusters according to a given similarity measure. Let c be an integer which represents the number of clusters with $2 \leq c \leq n$, where n is the number of data points. Define \mathbf{U} a partition matrix of elements μ_{ik} ($i = 1, 2, \dots, c, k = 1, 2, \dots, n$) which represents the degree of membership of data point j in fuzzy cluster i , such that:

$$\mu_{ik} \in [0, 1], \quad 1 \leq i \leq c, 1 \leq k \leq n, \quad (\text{IV.4})$$

$$\sum_{i=1}^c \mu_{ik} = 1 \quad \forall k, \quad (\text{IV.5})$$

$$0 < \sum_{k=1}^n \mu_{ik} < n \quad \forall i. \quad (\text{IV.6})$$

Given an integer m , define J_m as the sum of the squared errors weighted by the m^{th} power of the corresponding degree of membership, i.e.,

$$J_m(\mathbf{U}, \mathbf{v}) = \sum_{k=1}^n \sum_{i=1}^c (\mu_{ik})^m (d_{ik})^2, \quad (\text{IV.7})$$

where

$$d_{ik} = \|\mathbf{x}_k - \mathbf{v}_i\|, \quad (\text{IV.8})$$

and $\| \cdot \|$ is an inner product induced norm, m is a real number $\in [1, \infty)$ called the fuzzification constant (or weighting exponent), \mathbf{x}_k is a data point, and \mathbf{v}_i is the center of cluster i . The degrees of membership will be established by minimizing $J_m(\mathbf{U}, \mathbf{v})$. The goal of the fuzzy clustering algorithm is to determine the optimum degrees of membership μ_{ik} ($\forall i, k$) and the optimum fuzzy cluster centers \mathbf{v}_i ($\forall i$) such that the sum of the square errors J_m is minimum. The results of this minimization are given by (see [Ref. 43] and Appendix E for the derivation):

$$\mu_{ik} = \frac{1}{[\sum_{j=1}^c (\frac{d_{ik}}{d_{jk}})^{\frac{2}{m-1}}]} \quad \forall i, k, \quad (\text{IV.9})$$

$$\mathbf{v}_i = \frac{\sum_{k=1}^n (\mu_{ik})^m \mathbf{x}_k}{\sum_{k=1}^n (\mu_{ik})^m} \quad \forall i, \quad (\text{IV.10})$$

where Equation IV.9 is valid for a fixed \mathbf{V} ($\mathbf{V} = \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_c$), and Equation IV.10 is valid for a fixed \mathbf{U} . In multisensor-multitarget tracking systems, c is the number of targets, n is the total number of received measurements, \mathbf{x}_k is the s -dimensional measurement vector ($k = 1, 2, \dots, n$), and \mathbf{v}_i is the s -dimensional predicted vector for target i ($i = 1, 2, \dots, c$). The fuzzy c -means clustering algorithm or the Picard algorithm is guaranteed to converge to a local minimum [Ref. 44, 104].

The fuzzification constant m plays an important role. It reduces the influence of the measurement noise when computing the degrees of membership (Equation IV.9) and the cluster centers (Equation IV.10). The weighting exponent m reduces the influence of a small μ_{ik} (for data that are faraway from the cluster centers) compared to a large μ_{ik} (for data that are close to the cluster centers) [Ref. 83]. As m increases, its influence becomes stronger. For more details about the weighting exponent, see Windham [Ref. 107, 108].

D. PROPOSED FUZZY LOGIC DATA ASSOCIATION APPROACH

Suppose that n measurements are received at time index t (scan t). The number of measurements (n) does not necessarily equal the number of targets (c). It is required to assign (associate) only one of the n measurements to each target such that

each measurement can have only one origin. In data association, two types of errors can occur: missed correlation and incorrect correlation. In the case of a dense target environment in the presence of noise and other interference, the data association problem is the most critical problem in tracking systems. Gating techniques cannot solve the problem of associating measurements with tracks when a measurement falls within the gates of multiple target tracks or when multiple measurements fall within the gates of a target track, in which case a different technique is required. Our goal is to associate each measurement \mathbf{x}_k ($k = 1, 2, \dots, n$) with one of c possible tracks given predicted values \mathbf{v}_i for each track i , $i = 1, 2, \dots, c$. The target's predicted values \mathbf{v}_i can be estimated using optimal filtering techniques, such as least squares [Ref. 84], α - β tracker [Ref. 124] and Kalman filtering techniques [Ref. 7, 84, 85, 123]. The choice of a particular optimal filtering technique is not arbitrary but depends on the application and the assumed target state model.

The proposed fuzzy logic data association approach consists of the following steps:

1) Apply the *FCM* algorithm for a fixed \mathbf{V} and find the partition matrix \mathbf{U} , which represents the degrees of membership of all measurements to all tracks. The distance measures of Equation IV.8 are determined using the Euclidean norm as

$$d_{ik} = \sqrt{(\mathbf{x}_k - \mathbf{v}_i)'(\mathbf{x}_k - \mathbf{v}_i)}. \quad (\text{IV.11})$$

The association matrix \mathbf{U} represents the assignment matrix between all observations (measurements) and all entities (targets). Each element in the partition matrix μ_{ik} ($i = 1, 2, \dots, c$, $k = 1, 2, \dots, n$) represents an association measure between the predicted value of track i and measurement k .

2) Search for the maximum degree of membership $\mu_{i_M k_M}$ (the closest measurement-to-track pair) and make the indicated assignment, i.e., associate measurement k_M to track i_M .

- 3) Remove the measurement-to-track pair identified above from the assignment matrix \mathbf{U} and obtain the reduced matrix (this step is a virtual operation that aims to simplify the analysis and does not affect the values of the parameters $\mu_{ik}, \forall i, j$).
- 4) Repeat rules 2 and 3 for each remaining track until c measurements are assigned to the c existing tracks.
- 5) Obtain the final assignment of measurements to tracks.

To explain the above approach with the help of an example, suppose that there are four targets under surveillance in a given scan t ($c = 4$) with predicted vectors $\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3$, and \mathbf{v}_4 and four measurements $\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3$, and \mathbf{x}_4 ($n = 4$). We assume that the correct correlation is to assign measurement i to track i , $i = 1, 2, 3, 4$. Furthermore, assume that we apply the *FCM* algorithm for the given predicted vectors, using Equation IV.9, and the partition matrix is determined as:

$$\mathbf{U} = \begin{pmatrix} .25 & .55 & .15 & .21 \\ .10 & .25 & .05 & .12 \\ .60 & .05 & .70 & .27 \\ .05 & .15 & .10 & .40 \end{pmatrix}, \quad (\text{IV.12})$$

where the rows represent tracks and the columns represent measurements. We have $\mu_{i_M k_M} = \mu_{33} = 0.70$; thus measurement 3 is assigned to track 3. The reduced matrix is given by

$$\mathbf{U}_{red1} = \begin{pmatrix} .25 & .55 & .21 \\ .10 & .25 & .12 \\ .05 & .15 & .40 \end{pmatrix}. \quad (\text{IV.13})$$

In this case $\mu_{i_M k_M} = \mu_{12} = 0.55$; thus measurement 2 is assigned to track 1 and the reduced matrix will be

$$\mathbf{U}_{red2} = \begin{pmatrix} .10 & .12 \\ .05 & .40 \end{pmatrix}. \quad (\text{IV.14})$$

For the reduced matrix we have $\mu_{i_M k_M} = \mu_{44} = 0.40$; thus measurement 4 is assigned to track 4. Finally the reduced matrix U_{red3} will have the value 0.1 (μ_{21}), and measurement 1 is assigned to track 2. The final assignment of measurements to tracks is the following: measurement 1 is assigned to track 2 (incorrect correlation), measurement 2 is assigned to track 1 (incorrect correlation), measurement 3 is assigned to track 3 (correct correlation), and measurement 4 is assigned to track 4 (correct correlation). In this case we performed 2 correct correlations in a 4-target environment. Thus we performed 50% perfect data correlation in this example.

E. PERFORMANCE EVALUATION AND COMPARISON

Singh and Bailey [Ref. 58] proposed the first fuzzy logic approach for the data association problem. They applied their approach to the case of a two-dimensional multisensor-multitarget tracking system. Their approach performed 80% with respect to perfect correlation for the case of two targets with position standard deviations (3.760, 3.571 Ft) and speed standard deviations (0.835, 0.975 Ft/s).

Several examples are considered here to demonstrate the feasibility, simplicity, and efficiency of the proposed data association approach in a *MSMT* tracking system. In our simulation, the distance d_{ik} (Equation IV.8) is calculated using the Euclidean norm, and the degree of membership μ_{ik} (Equation IV.9) is calculated assuming $m = 2$. It is worth noting that we don't use the *FCM* iterations to derive the partition matrix **U**. Instead, we determine **U** directly from Equation IV.9 without any iteration. This is because the predicted vectors $\mathbf{v}_i (i = 1, 2, \dots, c)$ can be estimated using filtering techniques. Thus we fix **V** and apply Equation IV.8 and Equation IV.9 directly to determine **U**.

1. Two-Dimensional Tracking System

The first example considers the same example in [Ref. 58], in order to compare the results of the proposed approach under the same conditions. In this example, two targets are moving with constant acceleration, $a = 0.5 \text{ Ft/s}^2$, and sampling interval, $T = 1 \text{ s}$. For a given scan t , the target trajectories (Speeds and Positions) are

determined respectively as:

$$S_i(t) = S_i(t-1) + aT \text{ Ft/s}, \quad (\text{IV.15})$$

$$P_i(t) = P_i(t-1) + S_i(t) T \text{ Ft}, i = 1, 2. \quad (\text{IV.16})$$

At each scan, we have to associate a measurement to each target. The initial position and speed for target 1 are 9 Ft and 5 Ft/s respectively, and 100 Ft and 4 Ft/s for target 2. The measurement noise is assumed to be Gaussian with standard deviations 3.76 and 3.571 Ft for position and 0.835 and 0.975 Ft/s for speed. The true and the actual target positions and speeds are fuzzified using the *FCM* algorithm. The simulation was run for ten seconds (ten measurements), and the final assignments of measurements to tracks are performed using the steps mentioned in Section D.

The true target trajectories as well as the noisy measurements are shown in Figure 18. The fuzzification outputs are shown in Figure 19. The fuzzy output R_{ij} represents the degree of membership of measurement j to be originated from target i . The corresponding binary decisions are shown in Figure 20. The combined binary correlation results are shown in Figure 21. Figure 21 shows that the binary decisions for R_{11} and R_{22} are ones, and zeros for R_{12} and R_{21} (cross correlation). Thus the proposed approach correctly associates measurements to targets for all measurements and hence it achieves 100% perfect correlation (since all the cross correlations are zeros). The needed computations using the proposed approach are four elements and two comparisons. For the same example and using the method of [Ref. 58] the required computations are 100 *IF THEN* rules, defuzzification of 4 correlation tables, and 4 comparisons with a threshold. Furthermore, the approach of [Ref. 58] achieves only 80% perfect correlation in contrast to 100% perfect correlation using the proposed approach. The computational complexity is analyzed in details in Section F.

Example 2 considers the case of six targets. The results of this example are taken over 10,000 Monte Carlo simulations. The initial positions and speeds of the targets are [(9,5), (100,4), (30,7), (65,3.5), (45,2), (75,2)]. The standard deviations

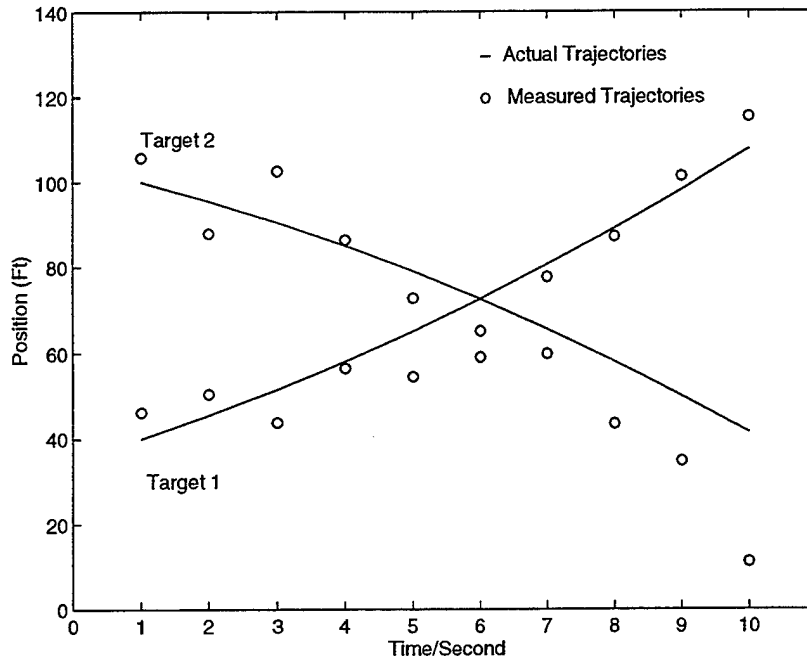


Figure 18. Actual and Measured Target Trajectories (Two Targets)

of positions are 3.65, 3.70, 3.75, 3.80, 3.90, and 4.0 Ft and that of speeds are 0.85, 0.9, 1, 1.1, 1.15, and 1.2 Ft/s. The true positions and speeds are the predicted values. Figure 22 depicts the true target trajectories. Figure 23 depicts the true target trajectories along with their sampled positions. All the position values in the figures are given in feet. The correlation results in terms of the degrees of membership are shown in Figures 24 and 25. The Y-axis represents the degree of fuzzy correlation variables ($R(i, i) = \mu_{ii}, i = 1, 2, \dots, 6$). The corresponding binary correlation values (hard data association) are shown in Figures 26 and 27. Figures 26 and 27 show that the proposed approach performs 100% (with respect to perfect correlation) for target 1, 100% for target 2, 100% for target 3, 90% for target 4, 90% for target 5, and 100% for target 6. Thus, on average, the proposed approach performs 96.67% with respect to perfect correlation. It performs 95.3% with respect to perfect correlation over 10,000 Monte Carlo simulations.

The fuzzy logic approach presented in [Ref. 58] performs 80% with respect to perfect correlation for two targets with approximately the same position and speed

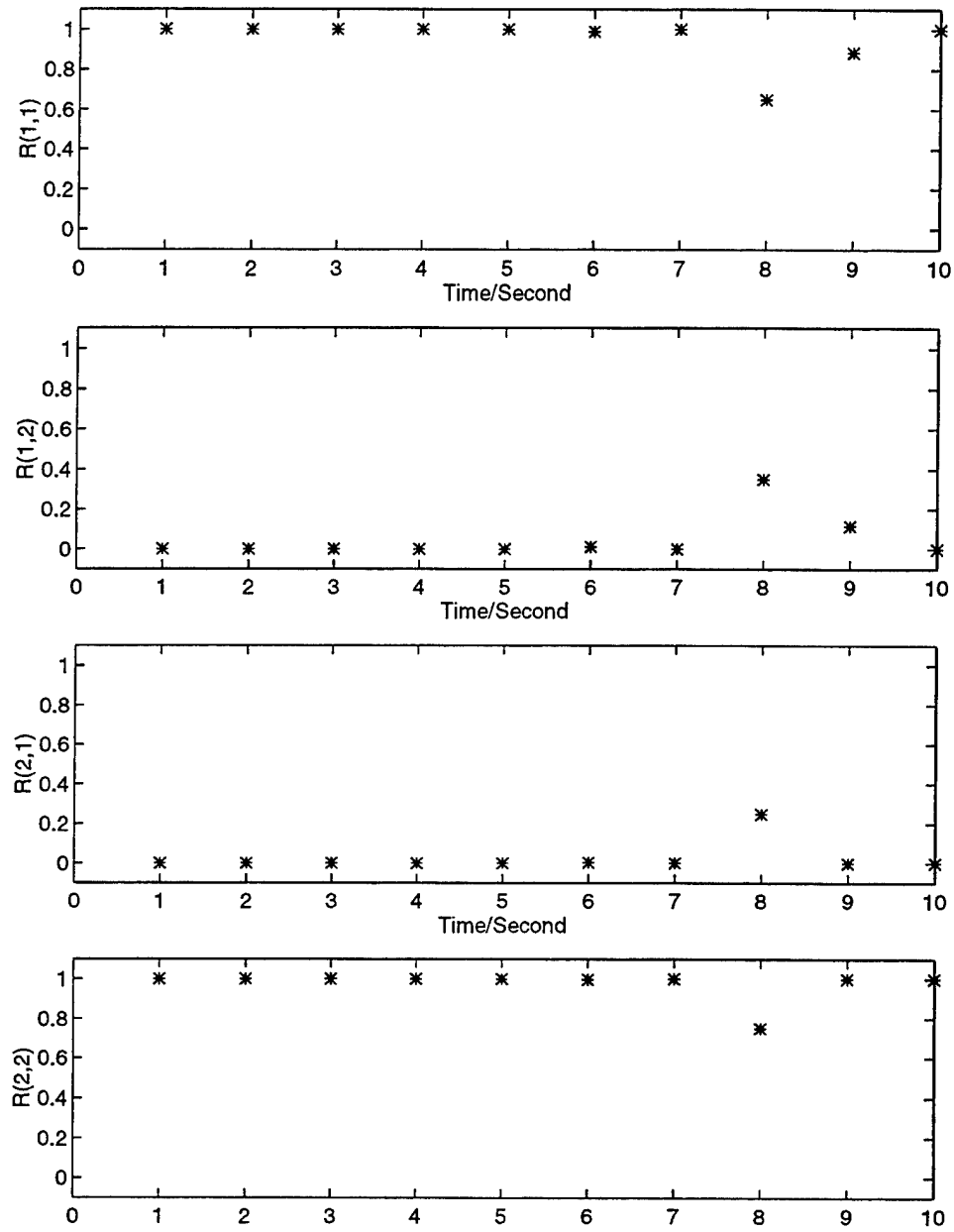


Figure 19. Fuzzy Correlation Outputs

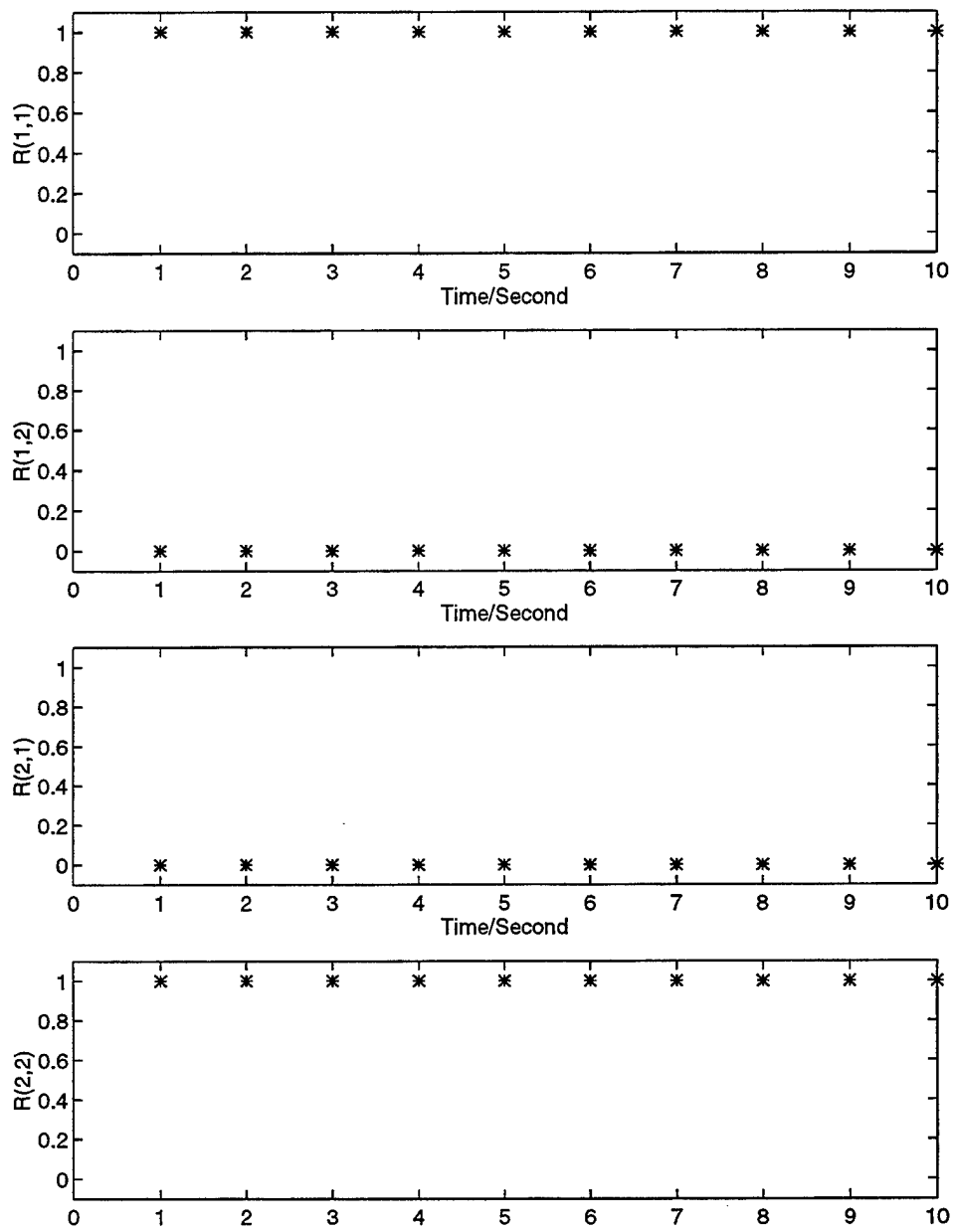


Figure 20. Binary (Hard) Correlation

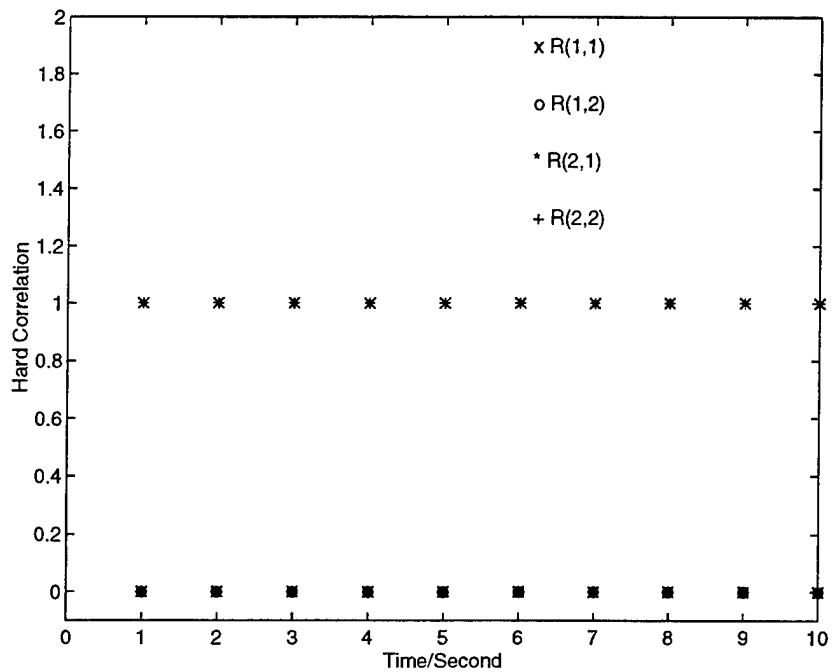


Figure 21. Combined Binary Correlation

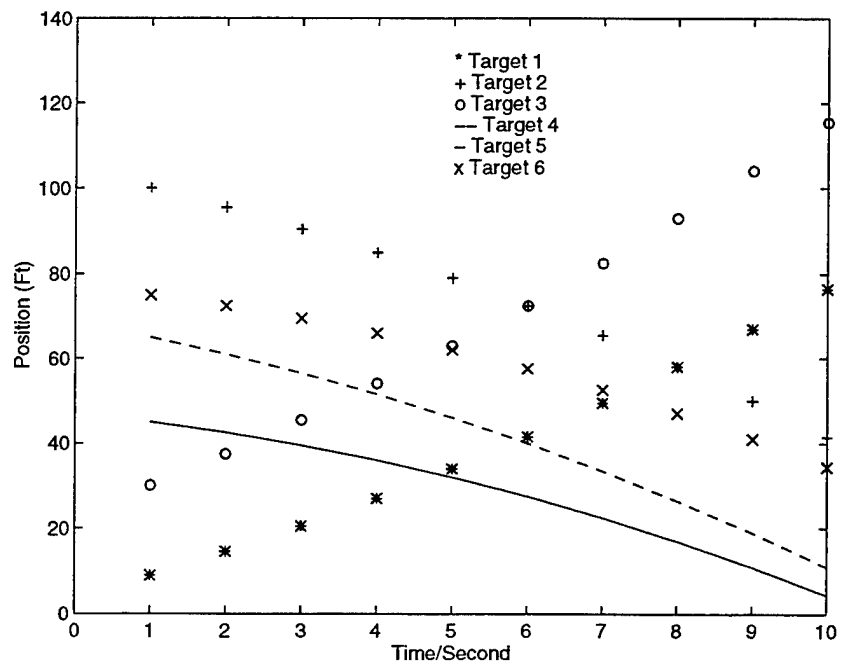


Figure 22. Actual Target Trajectories (Six Targets)

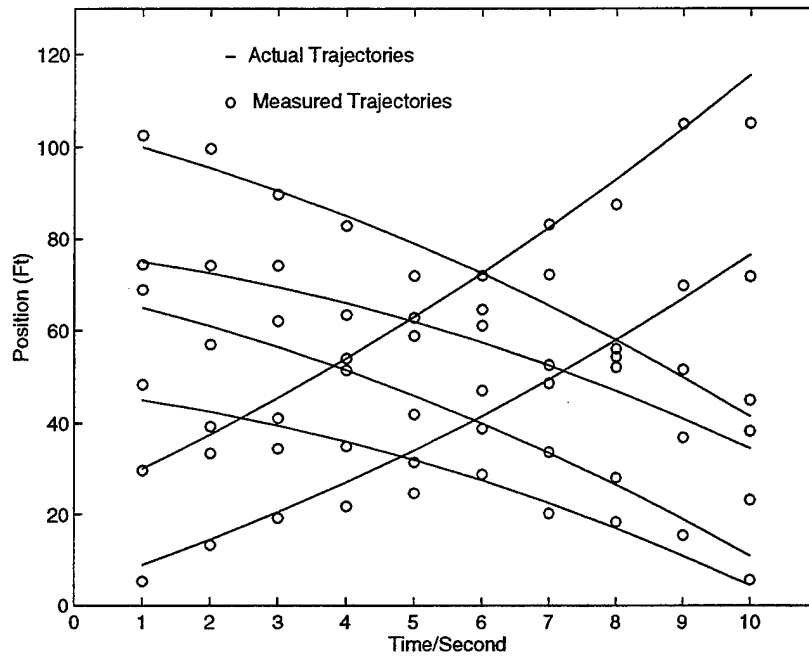


Figure 23. Actual and Measured Target Trajectories (Six Targets)

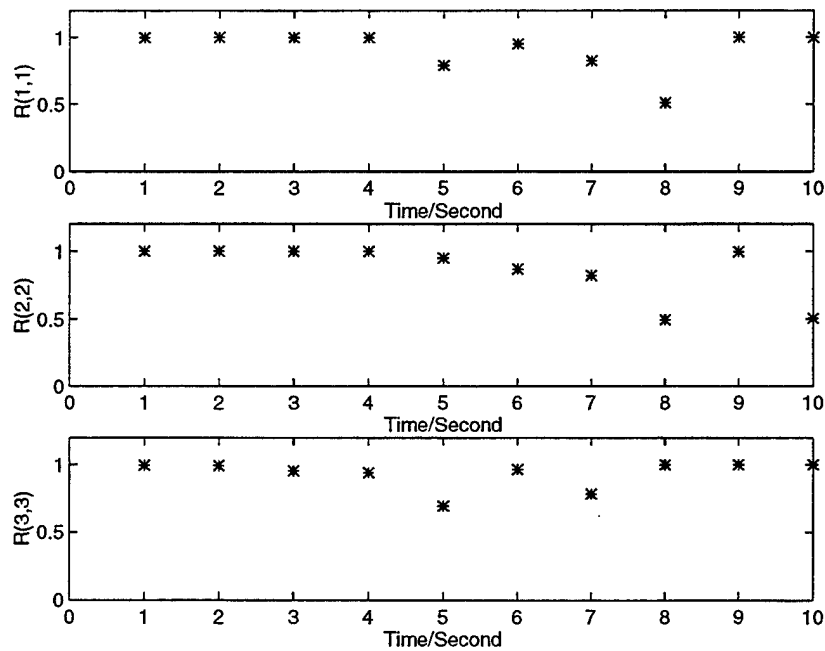


Figure 24. Fuzzy Correlation Membership Functions, $R(i, i), i = 1, 2, 3$

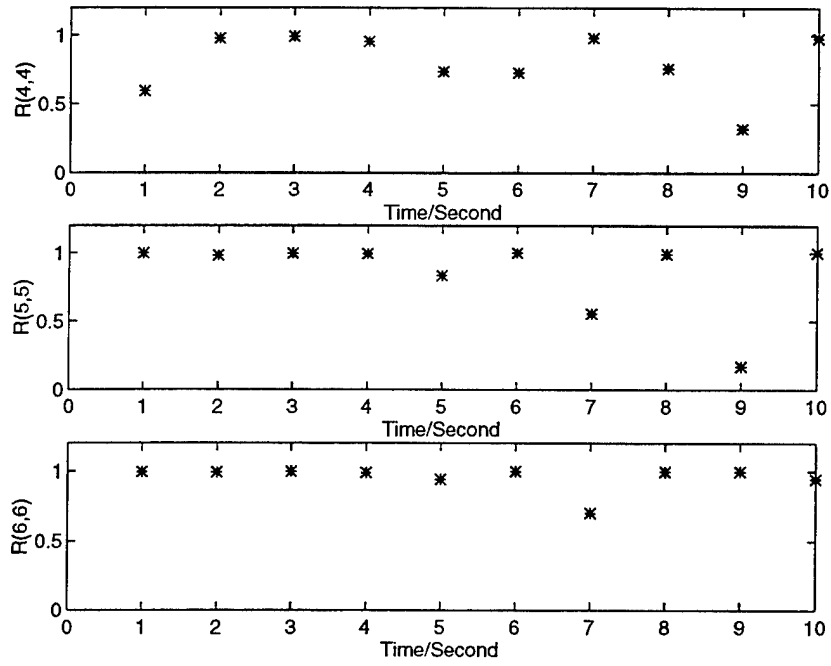


Figure 25. Fuzzy Correlation Membership Functions, $R(i,i), i = 4, 5, 6$

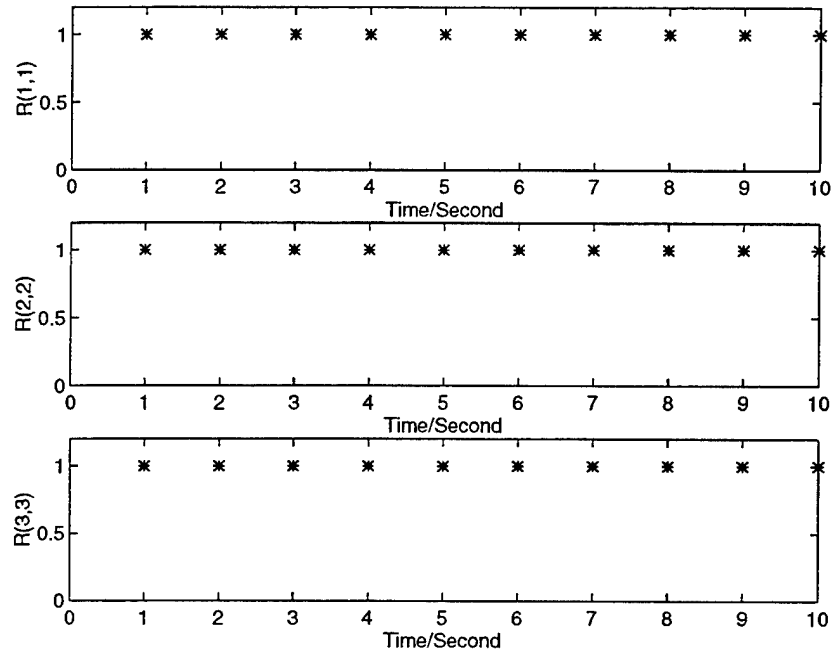


Figure 26. Hard Data Association, $R(i,i), i = 1, 2, 3$

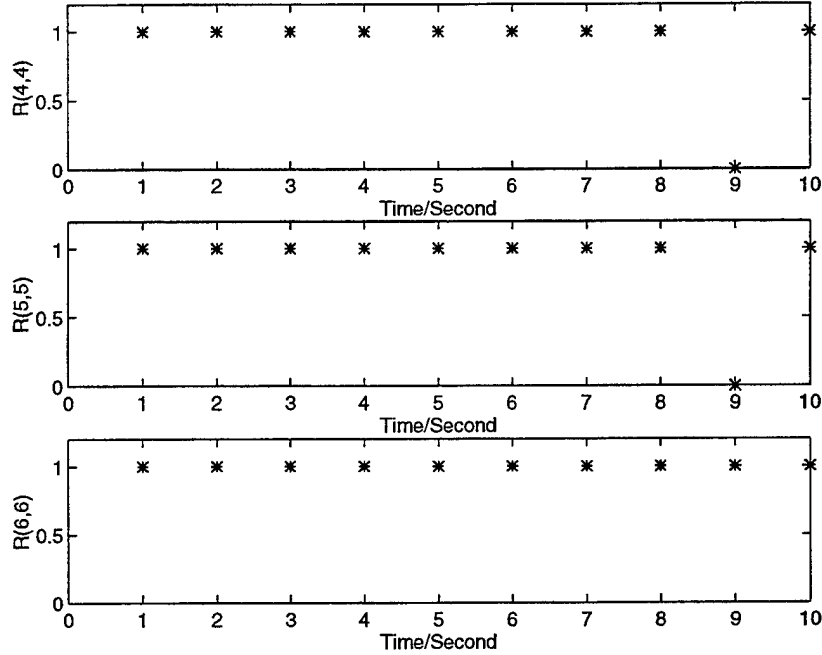


Figure 27. Hard Data Association, $R(i, i), i = 4, 5, 6$

uncertainties. To extend [Ref. 58] to the case of 6 targets; we have to (1) define 900 *IF THEN* rules that represent the fuzzy knowledge base, (2) use the centroid method for defuzzification of 36 correlation outputs, and (3) compare 36 correlation outputs with a threshold to obtain the hard data association outputs. The proposed approach only requires computation of a 6×6 partition matrix and thus reduces the computational complexity.

We extend example 2 to the case of eight crossing targets as shown in Figure 28. The initial conditions (Position and Speed) of the targets are [(9,5), (100,4), (30,7), (65,3.5), (45,2), (75,2), (20,5.5), (90,3) Ft, Ft/sec]. The positional standard deviations are 3.65, 3.70, 3.80, 3.90, 4.0, 4.10, 4.20, and 4.30 Ft. The standard deviations of speeds are 0.85, 0.90, 0.92, 0.97, 1.10, 1.20, 1.30, and 1.40 Ft/s. The true target trajectories as well as the sampled positions are shown in Figure 29. Due to the similarities of the results, only the percentage of perfect correlation is presented here. It is found that the proposed approach performs 87.87% with respect to perfect correlation over 10,000 Monte Carlo simulations.

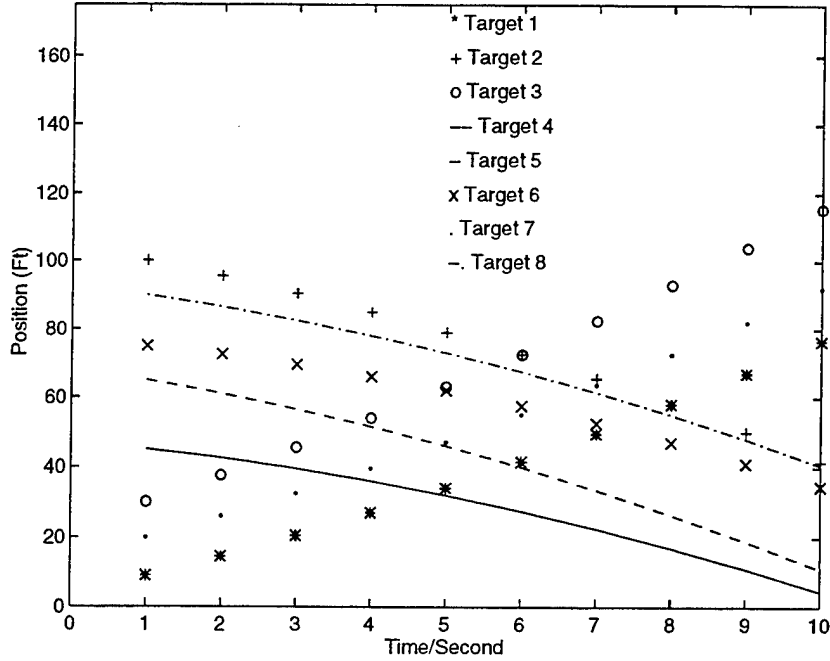


Figure 28. Actual Target Trajectories (Eight Targets)

It is worth noting that to extend [Ref. 58] to the case of eight targets, the number of *IF THEN* rules increases from 900 to 1600, the number of linguistic tables increases from 36 to 64, and the number of comparisons with a threshold increases from 36 to 64. Our approach deals only with an 8×8 partition matrix instead of 6×6 partition matrix thereby reducing the computational complexity in a dense target environment. The above results enable us to conclude that this approach is much more efficient than the other existing fuzzy logic data association approaches.

2. Four-Dimensional Tracking System

We consider a real example of moving targets in the x and y positions. The example considers the case of four crossing targets with measurements in x and y positions having noise standard deviation σ . The target's motion model is assumed to be determined as:

$$\mathbf{x}(t+1) = \mathbf{F} \mathbf{x}(t), \quad (\text{IV.17})$$

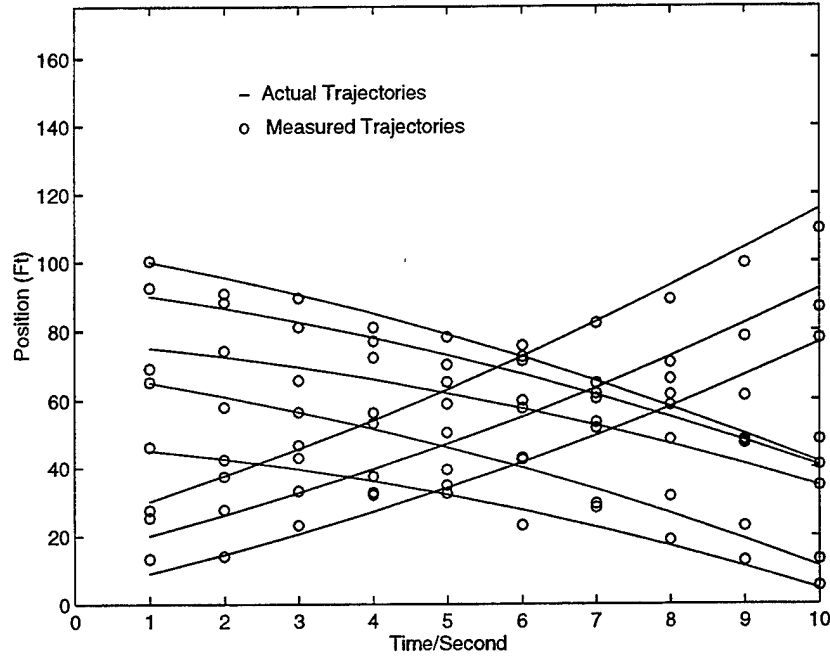


Figure 29. Actual and Measured Target Trajectories (Eight Targets)

where the state transition matrix

$$\mathbf{F} = \begin{pmatrix} 1 & T_s & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T_s \\ 0 & 0 & 0 & 1 \end{pmatrix}, \quad (\text{IV.18})$$

and T_s is the sampling interval. The 4×1 state vector $\mathbf{x}(t)$ contains the x and y target positions and velocities, i.e.,

$$\mathbf{x}(t) = \begin{pmatrix} x(t) \\ v_x(t) \\ y(t) \\ v_y(t) \end{pmatrix}. \quad (\text{IV.19})$$

The measurements are the x and y target positions given by

$$\mathbf{y}(t) = \mathbf{H}(t)\mathbf{x}(t) + \mathbf{w}(t), \quad (\text{IV.20})$$

where

$$\mathbf{H} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}. \quad (\text{IV.21})$$

The noise sequence $\mathbf{w}(t)$ is uncorrelated and Gaussian with zero mean and covariance matrix

$$\mathbf{C}_t = \text{Cov}(\mathbf{w}(t)) = \begin{pmatrix} \sigma^2 & 0 \\ 0 & \sigma^2 \end{pmatrix}, \quad (\text{IV.22})$$

where σ^2 is the variance of the measurement error in both x and y positions for all targets. In this example, we assume that x and y positions (measurements) are taken every 0.1 second and we process 150 samples. The cluster centers $\{\mathbf{v}_i\}$ are determined as the predicted target positions using the standard Kalman filter, which is usually implemented in practice. The true target trajectories along with the mean sampled positions over 1000 Monte Carlo simulations are depicted in Figures 30 and 31 for low ($\sigma = 5$ Ft) and high ($\sigma = 150$ Ft) noise levels, respectively. The correlation results in terms of the percentage of perfect correlation for different values of the noise standard deviation σ are shown in Figure 32 averaged over 1000 Monte Carlo simulations. The results indicate that the proposed approach achieves reasonable performance even in the presence of high level of measurement noise.

F. COMPUTATIONAL COMPLEXITY ANALYSIS

In this research, we define the computational complexity measure in terms of the number of rules used for defuzzification. In conventional fuzzy logic techniques, membership functions are represented by a number of linguistic variables ℓ (such as “small,” “medium,” “large,” etc.) These membership functions map the crisp data into ℓ fuzzy sets which define ℓ linguistic values. We assume that each measurement has dimension s , which represents the number of kinematic data and attributes, and the number of targets is equal to the number of measurements ($c = n$) for simplicity. The fuzzification of s input variables, each represented by ℓ linguistic

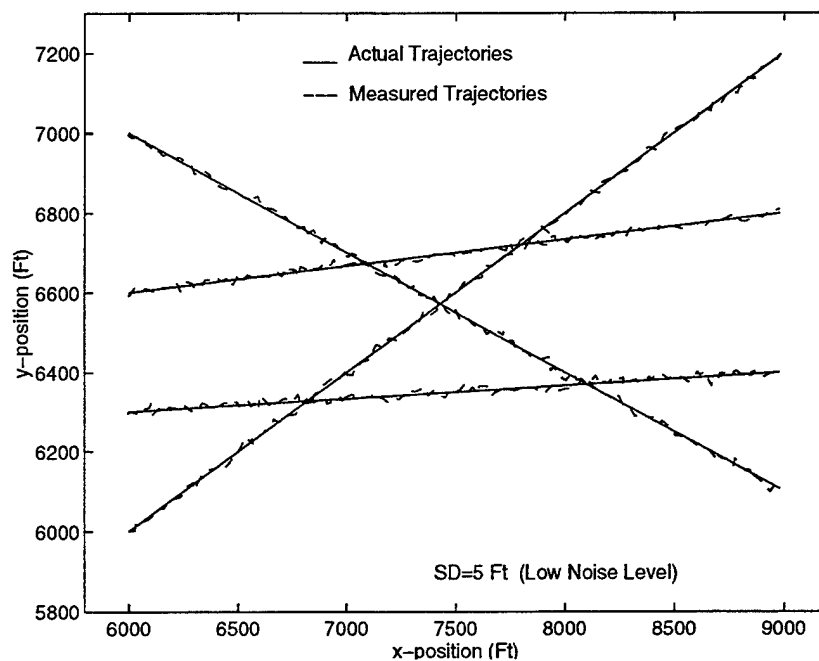


Figure 30. Actual and Mean Measured Trajectories for Low Noise Levels (Four Targets)

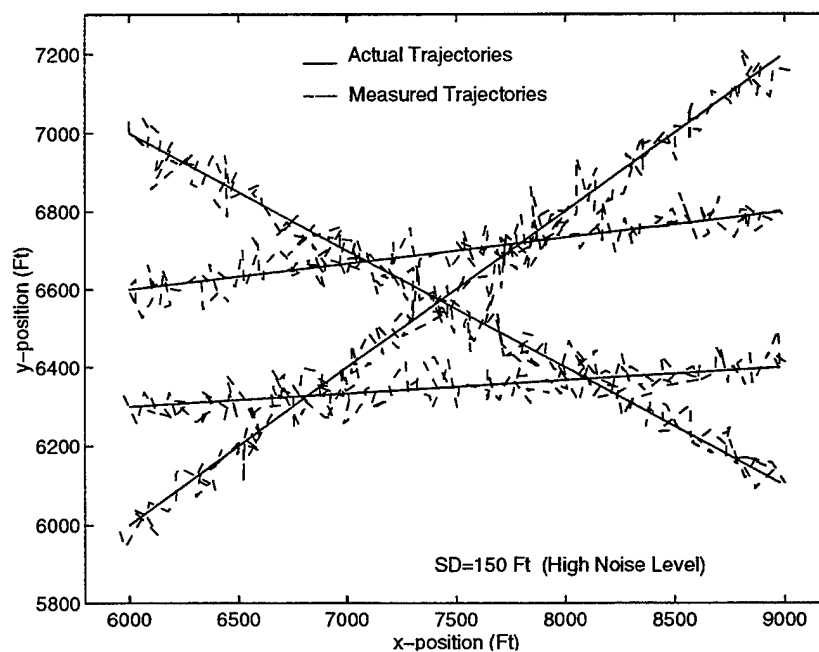


Figure 31. Actual and Mean Measured Trajectories for High Noise Levels (Four Targets)

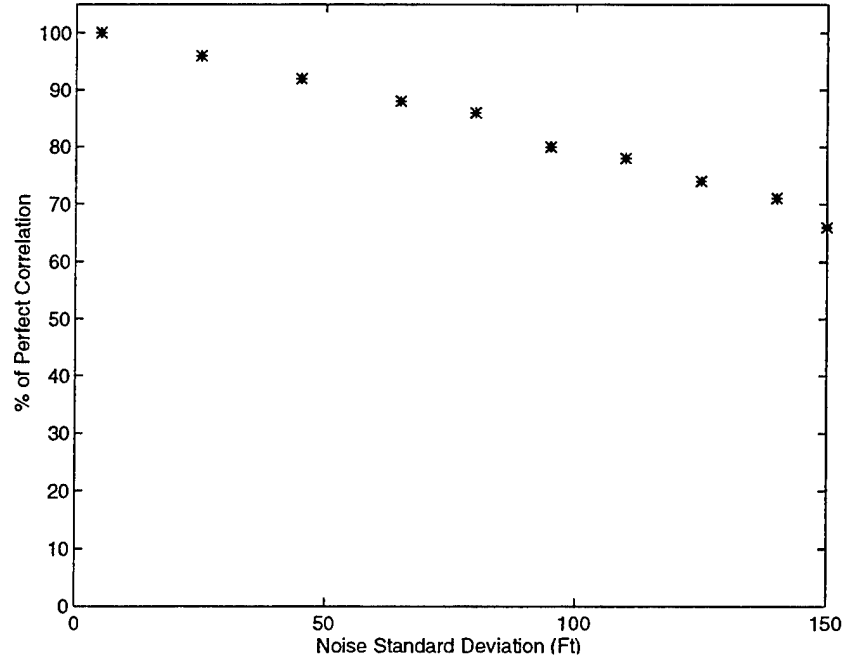


Figure 32. Percentage of Perfect Correlation for Different Values of Noise Standard Deviation

variables, requires N_R number of *IF THEN* rules, where [Ref. 58]

$$N_R = (\ell c)^s. \quad (\text{IV.23})$$

The outputs from the fuzzification represent the correlation between all measurements and all tracks and at each scan, we obtain $n \times c$ correlation outputs. Defuzzification is then performed to transform the fuzzy variables into non-fuzzy variables (binary-decision/hard-data association). This can be done by comparing the correlation outputs with a threshold. Since the computational cost for defuzzification is small ($n \times c$ comparisons) when compared to that of fuzzification ($(\ell \times c)^s$ rules), the computational cost for defuzzification is not taken into consideration. Thus the computation complexity using conventional fuzzy logic approaches is determined according to Equation IV.23.

In the proposed approach, we compute $\mu_{ik}, i = 1, 2, \dots, c, k = 1, 2, \dots, n$, using a number of vector inner product operations (Euclidean norm). Thus the required computation is to construct a partition matrix of dimension $c \times n$. The association

of the measurements to the tracks using the proposed approach is based only on the partition matrix by choosing the corresponding assignments of the maximum degrees of membership as described in Section D.

Tables IV - VII compare the required computations for different values of the parameters c , s , and ℓ . In each table we fix two parameters and use the third parameter as a variable. In all cases, the computational complexity using conventional fuzzy logic approaches is unfeasible. The proposed approach requires fewer computations and is feasible in all cases. As shown in Tables V - VII, adding a target (in case of conventional fuzzy logic systems), for a fixed number of linguistic and input variables, increases the number of rules from 27,000 to 42,857 to 64,000. Adding a linguistic variable, for a fixed number of targets and input variables, increases the number of rules from 27,000 to 46,656 to 74,088. Adding an input variable, for a fixed number of targets and linguistic variables, increases the number of rules from 27,000 to 810,000 to 24,300,000, which is the worst case. Based on the above observations, we remark that the proposed approach requires fewer computations compared to the existing fuzzy logic data association approaches.

Table IV. Comparison of the Computational Complexity, $c = 2, \dots, 12, s = 2, \ell = 5$

Fixed Parameters	Variable Parameter	Number of Rules Using Conventional Fuzzy Logic Systems (<i>IF THEN</i> Rules)	Required Computations Using The Proposed Approach (Dimension of Partition Matrix)
$s=2$ $\ell = 5$	$c = 2$	100	2×2
	$c = 3$	225	3×3
	$c = 4$	400	4×4
	$c = 5$	625	5×5
	$c = 6$	900	6×6
	$c = 7$	1225	7×7
	$c = 8$	1600	8×8
	$c = 9$	2025	9×9
	$c = 10$	2500	10×10
	$c = 11$	3025	11×11
	$c = 12$	3600	12×12

Table V. Comparison of the Computational Complexity, $c = 6, 7, 8, s = 3, \ell = 5$

Fixed Parameters	Variable Parameter	Number of Rules Using Conventional Fuzzy Logic Systems (<i>IF THEN</i> Rules)	Required Computations Using The Proposed Approach (Dimension of Partition Matrix)
$s=3$ $\ell = 5$	$c = 6$	27,000	6×6
	$c = 7$	42,875	7×7
	$c = 8$	64,000	8×8

Table VI. Comparison of the Computational Complexity, $c = 6, s = 3, \ell = 5, 6, 7$

Fixed Parameters	Variable Parameter	Number of Rules Using Conventional Fuzzy Logic Systems (<i>IF THEN</i> Rules)	Required Computations Using The Proposed Approach (Dimension of Partition Matrix)
$c=6$ $s=3$	$\ell = 5$	27,000	6×6
	$\ell = 6$	46,656	7×7
	$\ell = 7$	74,088	8×8

Table VII. Comparison of the Computational Complexity, $c = 6, s = 3, 4, 5, \ell = 5$

Fixed Parameters	Variable Parameter	Number of Rules Using Conventional Fuzzy Logic Systems (<i>IF THEN</i> Rules)	Required Computations Using The Proposed Approach (Dimension of Partition Matrix)
$c=6$ $\ell = 5$	$s = 3$	27,000	6×6
	$s = 4$	810,000	6×6
	$s = 5$	24,300,000	6×6

The problem of data association in multisensor multitarget tracking systems has been considered in this chapter. A nearest-neighbor fuzzy measurement-to-track association approach has been proposed based on the fuzzy clustering means algorithm. The association between measurements and tracks is determined using optimal membership functions derived from the fuzzy clustering means algorithm for fixed predicted vectors. The final assignment of measurements to tracks is obtained from the partition matrix determined based on the measurements and the tracks. Monte Carlo simulations demonstrated the effectiveness of the proposed approach. Performance is compared to perfect data association and other fuzzy association approaches. The results indicate that the proposed approach performs better than other methods. The proposed approach requires fewer computations than other fuzzy techniques.

V. AN ALL-NEIGHBOR FUZZY MEASUREMENT-TO-TRACK ASSOCIATION APPROACH

This chapter proposes a new all-neighbor fuzzy logic measurement-to-track association approach in distributed *MSMT* tracking systems. The proposed approach is developed based on fuzzy clustering means algorithm. The fuzzy clustering means algorithm determines the grade of membership of each received data point in each fuzzy cluster (see Chapter IV, Section C). Unlike other fuzzy logic data association algorithms, which assign only one observation to each track according to some association measure, the proposed all-neighbor fuzzy logic data association approach incorporates all observations within the gate of the predicted target state to update the state estimate using a membership weighted sum of innovations. To demonstrate the effectiveness of the proposed approach to perform data association in multisensor-multitarget environment, examples of a four-dimensional tracking system are considered. The performance is evaluated using Monte Carlo simulations and also compared to that of the nearest-neighbor standard filter and perfect data association. The results indicate that the proposed approach has better performance over a comparable nearest-neighbor standard filter and reasonable performance with respect to perfect data association.

A. POSSIBILITY AND PROBABILITY DISTRIBUTIONS

Uncertainty may be represented in several forms. Probability and possibility theories are two different formal systems employed for representing uncertainty. Bar-Shalom and Fortman [Ref. 7], developed the probabilistic data association filter which updates the predicted target state using a probability weighted sum of innovations (probabilistic score). A new approach proposed here associates measurements to track using a possibility score. This section highlights probability and possibility as different ways for representing uncertainty.

Zadeh [Ref. 41, 111] notes that probability is concerned with a measure of information while possibility is concerned with the meaning of information rather than its measure. A detailed discussion of both theories can be found in [Ref. 41, 42, 46, 63, 82, 83, 167, 176].

A fuzzy variable is associated with a possibility distribution in the same manner as a random variable is associated with a probability distribution [Ref. 41]. The theory of possibility is related to the theory of fuzzy sets by defining a possibility distribution on the values that may be assigned to a variable. Let X be a set of objects, and v is a variable on X . The statement “ v takes a value x ,” where x is an element in X , can be described by a membership function $\mu_A(x)$, which describes the degree to which the variable v takes a value x . The expression of a possibility distribution can be viewed as a membership function of the fuzzy set and can be handled by fuzzy set rules. The possibility distribution π over X describing the possibility that x is a value of v is defined to be numerically equal to the membership function $\mu(x)$ [Ref. 176]

$$\pi_X(x) = \mu(x). \quad (\text{V.1})$$

Thus possibility distribution and membership function both have the same mathematical expression.

The following discussion based on an example by Zadeh [Ref. 41] and Zimmermann [Ref. 83] clearly illustrates the difference between probability and possibility. Consider the statement “*Monterey has x foggy days in a week.*” A possibility distribution $\pi_X(x)$ may be associated with X by interpreting its values as the degrees of possibility with which X number of days can be foggy in Monterey. The important aspect of possibility distribution is that it is not statistical in nature. A probability distribution $f_X(x)$ may be associated with X by interpreting its values as the probabilities that Monterey can have x foggy days. The probability values can be determined in a statistical manner by observing meteorological data for several seasons. Hypothetical values of $\pi_X(x)$ and $f_X(x)$ might be as shown in Table VIII. A high/low degree of possibility does not imply a high/low degree of probability. However, if an

Table VIII. An Example of Possibility and Probability Distributions

v	1	2	3	4	5	6	7
$\pi_X(x)$	1	1	1	1	0.8	0.6	0.4
$f_X(x)$	0.1	0.8	0.1	0	0	0	0

event is impossible, it is also improbable. Thus, in a heuristic way, possibility is an upper bound for probability.

1. Possibility/Probability Consistency Principle

The probability/possibility consistency principle is a heuristic observation that a lessening of the possibility of an event tends to lessen its probability but not vice versa. Zadeh [Ref. 41] establishes the possibility/probability consistence principle as the degree of consistency between the probability distribution $f_X(x)$ and the possibility distribution $\pi_X(x)$.

Consider that $X = \{x_1, x_2, \dots, x_n\}$ with corresponding possibilities $\pi_X(x) = (\pi_1, \pi_2, \dots, \pi_n)$ and probabilities $f_X(x) = (p_1, p_2, \dots, p_n)$. The degree of consistency between the probability distribution $f_X(x)$ and the possibility distribution $\pi_X(x)$ is expressed by a consistency measure [Ref. 41]

$$C(\pi_X, f_X) = \pi_1 p_1 + \pi_2 p_2 + \dots + \pi_n p_n = \sum_{x \in X} \pi_x f_X, \quad (\text{V.2})$$

where $C(\pi_X, f_X)$ is in the range $[0, 1]$.

Suppose that $X = \{x_1, x_2, x_3, x_4, x_5\}$, $f_X(x)$ is a probability distribution and $\pi_1(x)$, $\pi_2(x)$ and $\pi_3(x)$ are three possibility distributions with values and corresponding consistency degrees as shown in Table IX. The degrees of consistency in Table IX show that there is no contradiction between $\pi_1(x)$ and $f_X(x)$. In this case we obtain x_3 , x_4 and x_5 with probability equal to $\frac{1}{3}$, and x_3 , x_4 and x_5 are possible results. On

Table IX. A Probability Distribution and Three Possibility Distributions

	x_1	x_2	x_3	x_4	x_5	$C(\pi_X, f_X)$
$p(x_i)$	0	0	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	
$\pi_1(x_i)$	0	0	1	1	1	1
$\pi_2(x_i)$	1	1	0	0	0	0
$\pi_3(x_i)$	0	0	0.5	0.5	0.5	0.5

the other hand, $\pi_2(x)$ and $f_X(x)$ are inconsistent while $C(\pi_3(x), f_X(x))$ indicates a degree of consistency 0.5.

2. Uncertainty and Fuzziness

The probability theory deals with randomness which describes the uncertainty with regard to the occurrence of an object. The fuzzy set theory deals with fuzziness which describes ambiguity and imprecision of the meaning of an object. Randomness determines the probability of occurrence of an event (it may or may not occur). Fuzziness determines the degree of membership that an event occurs (not whether it occurs) [Ref. 82]. Both randomness and fuzziness describe uncertainty numerically in the unit interval $[0, 1]$. They combine sets associatively, distributively, and commutatively. The main dissimilarity between them is how both systems treat a set A and its complement A^c . In probability theory: $A \cap A^c = \emptyset$, $A \cup A^c = X$, $P(A \cap A^c) = P(\emptyset) = 0$, and $P(A \cup A^c) = P(X) = 1$, where \emptyset is null event and X is a set of objects. In fuzzy set theory: $A \cap A^c \neq \emptyset$, $A \cup A^c \neq X$, $A \cup B = \max(A, B)$, $A \cap B = \min(A, B)$, and $\bar{A} = 1 - A$.

3. Fuzzy Subsethood Theorem

Kosko [Ref. 82] addressed the following important question: does the degree of membership to which an element belongs to a fuzzy set equal the probability that the same element belongs to the same set. Toward this direction, Kosko developed the fuzzy Subsethood theorem, which implies the Bayes theorem or, equivalently, probabilities represent a special case of fuzziness. Buede [Ref. 162] compared fuzzy set and Bayes approaches for target identification in a data fusion system. Buede showed that the results of fuzzy set theorem are inferior to those of probability. This result is expected since the probability approach utilizes *a priori* information about the underlying process. Buede [Ref. 162] also showed that sometimes the results of both approaches are similar and sometimes they are dissimilar. This depends on the available data and the application.

The subsethood between two sets A and B , denoted by $S(A, B)$, represents the degree to which set A belongs to set B and is given by [Ref. 82]

$$S(A, B) = \frac{M(A \cap B)}{M(A)}, \quad (\text{V.3})$$

where

$$M(A) = \sum_i \mu_A(x_i) \quad (\text{V.4})$$

is called the cardinality of A and $\mu_A(x_i)$ is the degree of membership of an element x_i in set A . Since $S(A, B)$ has the same form as the conditional probability, the subsethood theorem implies Bayes theorem [Ref. 82].

B. PROPOSED ALL-NEIGHBOR FUZZY ASSOCIATION APPROACH

In this section, we propose a new all-neighbor fuzzy logic association approach. The proposed approach associates measurements to tracks using a possibility score. The possibility score is determined as a degree of membership using fuzzy clustering means algorithm. Nearest-neighbor fuzzy data association algorithms reported in the literature [Ref. 11, 14, 58] consist of four steps: 1) fuzzification of crisp data into

fuzzy variables, 2) formation of fuzzy knowledge base containing IF-THEN rules and fuzzy statements, 3) development of a fuzzy inference mechanism simulating human decision making process to generate output fuzzy variables, and 4) defuzzification of fuzzy variables into crisp data. The proposed approach performs all-neighbor data association based on the similarity measures of data (measurements) in fuzzy clusters (targets).

Suppose that there are c targets under surveillance and N_v number of valid observations $\{\mathbf{y}_1(k), \mathbf{y}_2(k), \dots, \mathbf{y}_n(k)\}$ within the target gates received at scan k . The number of validated observations N_v is not necessarily equal to the number of targets (clusters). The motion model of each target i is assumed to be

$$\mathbf{x}_i(k+1) = \mathbf{F}_i \mathbf{x}_i(k) + \mathbf{g}_i(k), i = 1, 2, \dots, c, \quad (\text{V.5})$$

where $\mathbf{x}_i(k)$ is an n dimensional state vector at time instant k , \mathbf{F}_i is an $n \times n$ state transition matrix, and $\mathbf{g}_i(k)$ is a noise input sequence (plant noise). The measurement equation is modeled as

$$\mathbf{y}_i(k) = \mathbf{H}_i(k) \mathbf{x}_i(k) + \mathbf{w}_i(k), i = 1, 2, \dots, c, \quad (\text{V.6})$$

where $\mathbf{y}_i(k)$ is an M dimensional measurement vector, $\mathbf{H}_i(k)$ is an $M \times n$ measurement matrix, and $\mathbf{w}_i(k)$ is a measurement noise vector. The plant noise and the measurement noise sequences are assumed to be uncorrelated, zero mean Gaussian sequences with the corresponding covariance matrices

$$\mathbf{Q}_i(k) = \text{Cov}(\mathbf{g}_i(k)), \quad (\text{V.7})$$

$$\mathbf{C}_i(k) = \text{Cov}(\mathbf{w}_i(k)). \quad (\text{V.8})$$

The weighted least squares prediction of the state vector and the corresponding covariance matrix for each target are obtained for the next measurement time as follows [Ref. 3, 7]

$$\hat{\mathbf{x}}_i(k+1 | k) = \mathbf{F}_i(k)\hat{\mathbf{x}}_i(k | k), \quad (\text{V.9})$$

$$\mathbf{P}_i(k+1 | k) = \mathbf{F}_i(k)\mathbf{P}_i(k | k)\mathbf{F}_i'(k) + \mathbf{Q}_i(k). \quad (\text{V.10})$$

Using the results of the fuzzy clustering means algorithm (Chapter IV, Section C), a cost function $J_m(\mathbf{U}, \hat{\mathbf{y}})$ is defined as the sum of the squared errors weighted by the m^{th} power of the corresponding degree of membership, i.e.,

$$J_m(\mathbf{U}, \hat{\mathbf{y}}) = \sum_{j=1}^{N_v} \sum_{i=1}^c (\mu_{ij})^m (d_{ij})^2, \quad (\text{V.11})$$

$$(d_{ij})^2 = \| \mathbf{y}_j - \hat{\mathbf{y}}_i \|^2, \quad (\text{V.12})$$

where $\| \cdot \|$ is an inner product induced norm and m is fuzzification constant in the range $\in [1, \infty)$. Equation V.12 represents the distance between measurement j and target i . For a set of predicted measurements $(\hat{\mathbf{y}}_1(k+1 | k), \hat{\mathbf{y}}_2(k+1 | k), \dots, \hat{\mathbf{y}}_c(k+1 | k))$, the degrees of membership of all observations to all tracks, $\{\mu_{ij}\}$, can be determined such that the sum of the square errors $J_m(\mathbf{U}, \hat{\mathbf{y}})$ is minimum. The results are obtained using the fuzzy clustering means algorithm [Ref. 43, 44] (see Chapter IV, Section C) as:

$$\mu_{ij} = \frac{1}{[\sum_{s=1}^c (\frac{d_{ij}}{d_{sj}})^{\frac{2}{m-1}}]} \quad \forall i, j, \quad (\text{V.13})$$

where the distance of Equation V.12 is obtained as the Euclidean norm

$$d_{ij} = \sqrt{(\mathbf{y}_j - \hat{\mathbf{y}}_i)'(\mathbf{y}_j - \hat{\mathbf{y}}_i)}, \quad (\text{V.14})$$

and μ_{ij} represents the degree of possibility that an observation j is originated from target i . The membership values are normalized such that, for a given track i , the contributions of all observations equal unity, i.e.,

$$\sum_{j=1}^{N_v} \mu_{ij} = 1, \quad i = 1, 2, \dots, c. \quad (\text{V.15})$$

The state estimate of target i is updated based on the new measurement according to [Ref. 3, 7]

$$\hat{\mathbf{x}}_i(k+1 | k+1) = \hat{\mathbf{x}}_i(k+1 | k) + \mathbf{W}_i(k+1) \sum_{j=1}^{N_v} \mu_{ij} \tilde{\mathbf{y}}_{ij}(k+1), \quad i = 1, \dots, c, \quad (\text{V.16})$$

where $\tilde{\mathbf{y}}_{ij}(k+1)$ is the innovation due to observation j and target i at time instant $(k+1)$, given by

$$\tilde{\mathbf{y}}_{ij}(k+1) = \mathbf{y}_j(k+1) - \hat{\mathbf{y}}_i(k+1), \quad (\text{V.17})$$

and $\mathbf{W}_i(k+1)$ is the Kalman filter gain of target i . The state update equation can be rewritten as:

$$\hat{\mathbf{x}}_i(k+1 | k+1) = \hat{\mathbf{x}}_i(k+1 | k) + \mathbf{W}_i(k+1) \tilde{\mathbf{y}}_i(k+1), \quad (\text{V.18})$$

where

$$\tilde{\mathbf{y}}_i(k+1) = \sum_{j=1}^{N_v} \mu_{ij} \tilde{\mathbf{y}}_{ij}(k+1) \quad (\text{V.19})$$

is the sum of all weighted innovations. The updated covariance matrix can be obtained as [Ref. 7] (see Appendix E for the derivation):

$$\mathbf{P}_i(k+1 | k+1) = \mathbf{P}_{i1}(k+1 | k+1) + \tilde{\mathbf{P}}_{i2}(K+1), \quad (\text{V.20})$$

where

$$\mathbf{P}_{i1}(k+1 | k+1) = [\mathbf{I} - \mathbf{W}_i(k+1)\mathbf{H}_i(k+1)]\mathbf{P}_i(k+1 | k) \quad (\text{V.21})$$

is the standard covariance update equation, and

$$\tilde{\mathbf{P}}_{i2}(k+1) = \mathbf{W}_i(k+1) \left[\sum_{j=1}^{N_v} \mu_{ij} \tilde{\mathbf{y}}_{ij}(k+1) \tilde{\mathbf{y}}_{ij}'(K+1) - \tilde{\mathbf{y}}_i(k+1) \tilde{\mathbf{y}}_i'(k+1) \right] \mathbf{W}_i'(K+1). \quad (\text{V.22})$$

If there is no observation within the gate of target i , the updated state estimate and the covariance matrix will be simply the previous ones, i.e.,

$$\hat{\mathbf{x}}_i(k+1 | k+1) = \hat{\mathbf{x}}_i(k+1 | k), \quad (\text{V.23})$$

$$\mathbf{P}_i(k+1 | k+1) = \mathbf{P}_i(k+1 | k). \quad (\text{V.24})$$

Noting that Equation V.12 is valid for any inner-product-induced norm metric, Equation V.11 can be written as

$$J_m(\mathbf{U}, \hat{\mathbf{y}}, \mathbf{G}) = \sum_{j=1}^{N_v} \sum_{i=1}^c (\mu_{ij})^m (d_{ij})_G^2, \quad (\text{V.25})$$

where square of the weighted distance is given by

$$(d_{ij})_G^2 = (\mathbf{y}_j - \hat{\mathbf{y}}_i)' \mathbf{G} (\mathbf{y}_j - \hat{\mathbf{y}}_i), \quad (\text{V.26})$$

and \mathbf{G} is any positive-definite matrix [Ref. 43]. It is convenient to choose \mathbf{G} to be related to the covariance matrix of the measurement error such that the larger the measurement error the larger is the distance (the smaller is the degree of membership) and vice versa. Based on this observation, we choose $\mathbf{G} = \mathbf{C}^{-1}$, where \mathbf{C} is the measurement noise covariance matrix defined by Equation V.8.

C. SIMULATION RESULTS

Two examples are presented to study the performance of the proposed all-neighbor fuzzy logic data association algorithm in *MSMT* tracking systems.

1. Simulation Example 1: Moving Targets Without Acceleration

The first example considers the case of two crossing targets without acceleration. The target's motion model is assumed to be :

$$\mathbf{x}(k+1) = \mathbf{F} \mathbf{x}(k), \quad (\text{V.27})$$

where the state transition matrix

$$\mathbf{F} = \begin{pmatrix} 1 & T_s & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T_s \\ 0 & 0 & 0 & 1 \end{pmatrix}, \quad (\text{V.28})$$

and T_s is the sampling interval. The state vector $\mathbf{x}(k)$ contains the x and y target positions and velocities:

$$\mathbf{x}(k) = \begin{pmatrix} x(k) \\ v_x(k) \\ y(k) \\ v_y(k) \end{pmatrix}. \quad (\text{V.29})$$

The measurements are the x and y target positions, i.e.,

$$\mathbf{y}(k) = \mathbf{H}(k)\mathbf{x}(k) + \mathbf{w}(k), \quad (\text{V.30})$$

where the measurement matrix

$$\mathbf{H} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}. \quad (\text{V.31})$$

Measurements are affected by noise, which is modeled as zero mean Gaussian with standard deviation σ . The noise sequence $\mathbf{w}(k)$ has covariance matrix

$$\mathbf{C} = \text{Cov}(\mathbf{w}(k)) = \begin{pmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{pmatrix}, \quad (\text{V.32})$$

where σ_x^2 and σ_y^2 are the variances of the measurement errors in x and y positions, respectively. The overall measurement error is computed as

$$e = \sqrt{(x_{true} - \hat{x})^2 + (y_{true} - \hat{y})^2}. \quad (\text{V.33})$$

In this example, we assume that x and y positions are measured every 0.1 second, with measurement uncertainties $\sigma_{x1}=\sigma_{y1}= 150$ meters and $\sigma_{x2}=\sigma_{y2}= 200$ meters. The initial target states (actual trajectories) are assumed to be

$$\mathbf{x}_{t1}(0) = \begin{pmatrix} 6000 \text{ m} \\ 158.9 \text{ m/sec} \\ 6000 \text{ m} \\ 3.3 \text{ m/sec} \end{pmatrix}, \quad (\text{V.34})$$

$$\mathbf{x}_{t_2}(0) = \begin{pmatrix} 6000 \text{ m} \\ 158.9 \text{ m/sec} \\ 6050 \text{ m} \\ -3.3 \text{ m/sec} \end{pmatrix}. \quad (\text{V.35})$$

In each scan, we receive two measurements from two targets. The proposed all-neighbor approach updates the state estimate of each target track using the received measurements.

In the nearest-neighbor standard filter [Ref. 3, 7], the nearest observation that maximizes the likelihood function of the residual error associated with the selection is used to update the target's track. Maximization of the likelihood function is equivalent to minimization of the following distance [Ref. 3]:

$$d^2 = d_{ij}^2 + \ell n |S_i|, \quad (\text{V.36})$$

where the weighted sum of innovation

$$d_{ij}^2 = [\mathbf{y}_j - \hat{\mathbf{y}}_i]' \mathbf{S}_i^{-1} [\mathbf{y}_j - \hat{\mathbf{y}}_i], \quad (\text{V.37})$$

and the residual covariance matrix

$$\mathbf{S}_i = \mathbf{H} \mathbf{P} \mathbf{H}' + \mathbf{C}. \quad (\text{V.38})$$

In this case, each target i is updated using the measurement that has the minimum distance d_{ij} .

We process 150 measurements (15 seconds of data) over a 50-run Monte Carlo simulation. The actual target trajectories are simulated according to Equation V.27 given the initial target states from Equations V.34 and V.35. The measured target trajectories are obtained by adding noise to the true target trajectories with the following covariance structure (Equation V.32):

$$\mathbf{C}_1 = \text{Cov}(\mathbf{w}_1(k)) = \begin{pmatrix} 60^2 & 0 \\ 0 & 60^2 \end{pmatrix}, \quad (\text{V.39})$$

$$\mathbf{C}_2 = Cov(\mathbf{w}_2(k)) = \begin{pmatrix} 90^2 & 0 \\ 0 & 90^2 \end{pmatrix}. \quad (\text{V.40})$$

The measured target trajectories (dashed lines) along with the actual target trajectories (solid lines) are shown in Figure 33. The estimated target tracks (solid curves) using the proposed approach (Equation V.18) along with the actual target trajectories (dashed curves) are shown in Figure 34. The overall measurement error for each target, evaluated using Equation V.33, is shown in Figure 35. The estimated target tracks and the overall measurement errors are evaluated based on a 50-run Monte Carlo simulation. Figures 36- 39 show the results of tracking using the nearest-neighbor standard filter and perfect data association. The perfect data association represents the correct association between all received measurements and all targets and determines the lower bound of the estimation error [Ref. 3, 7]. As shown in Figures 34 and 36, the proposed fuzzy approach correctly tracks both targets while the nearest-neighbor standard filter loses both targets due to the high rate of incorrect association (since the two targets are too close to each other). As shown in Figures 35, 37, and 39, the steady measurement error of the proposed approach is 13.7 as opposed to 29.5 and 12.9 in case of nearest-neighbor standard filter and perfect data association, respectively.

The results of this example show that the proposed approach successfully tracks both targets and has better performance than a comparable nearest-neighbor standard filter and a reasonable performance with respect to perfect data association.

2. Simulation Example 2: Maneuvering Targets

Here we consider three maneuvering targets. The target motion model is assumed to be

$$\mathbf{x}(k+1) = \mathbf{F} \mathbf{x}(k) + \mathbf{g}(k), \quad (\text{V.41})$$

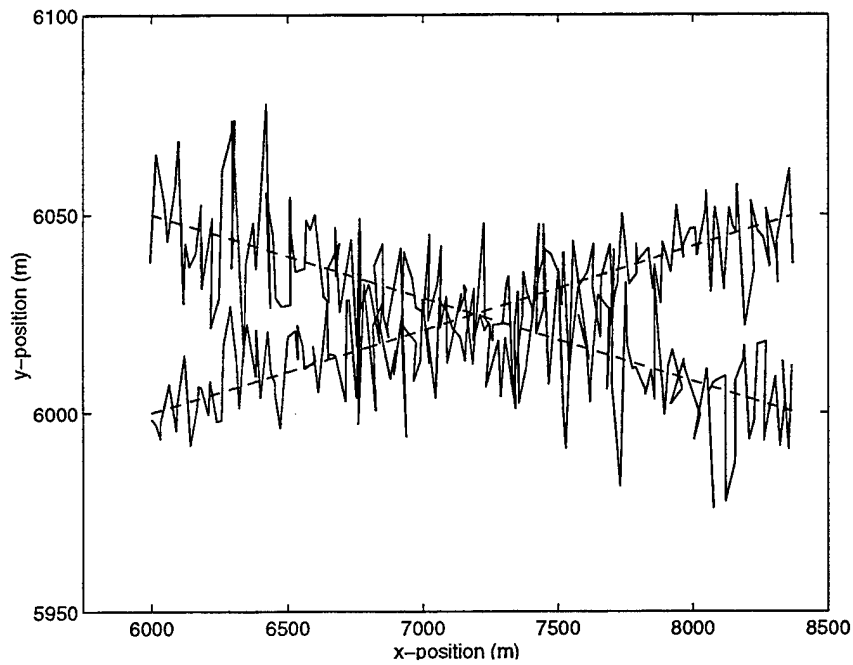


Figure 33. Actual and Mean Measured Target Trajectories

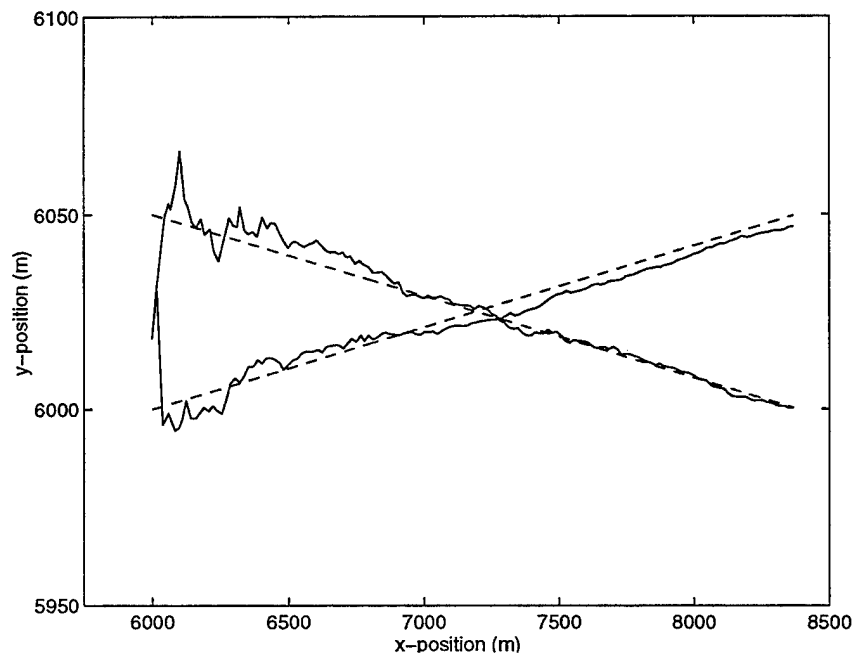


Figure 34. Actual and Mean Estimated Tracks: Fuzzy Approach

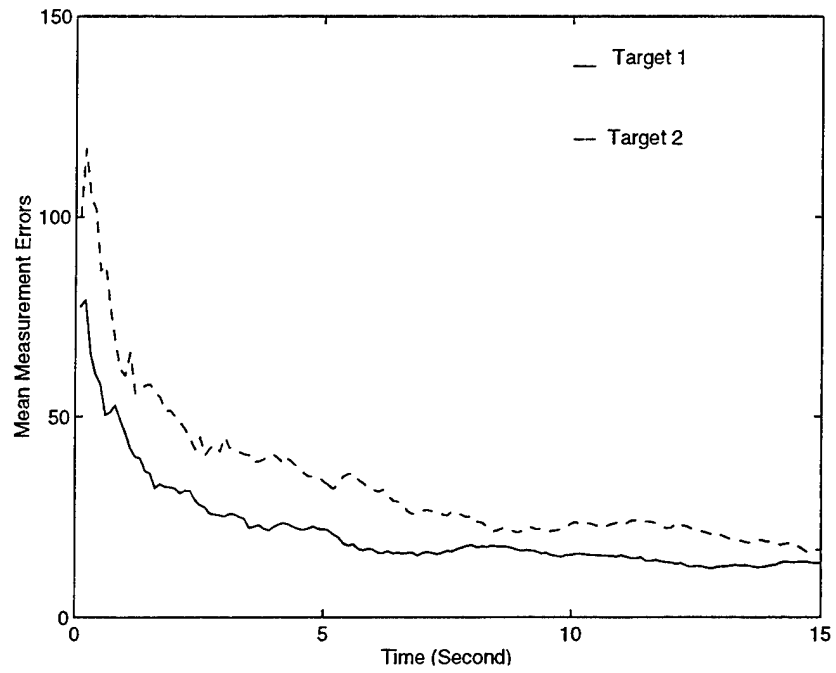


Figure 35. Mean Measurement Errors: Fuzzy Approach

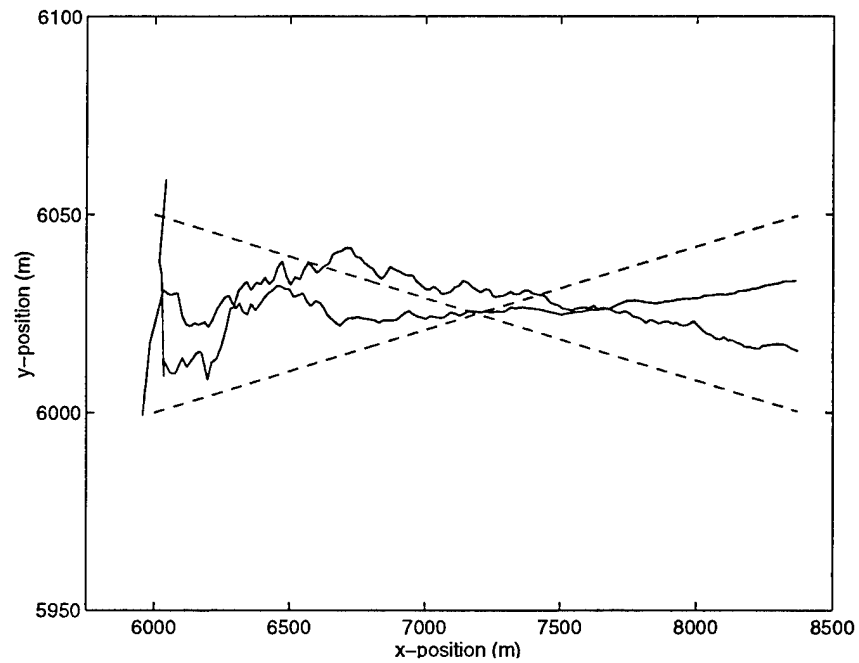


Figure 36. Actual and Mean Estimated Tracks: Nearest-Neighbor Standard Filter

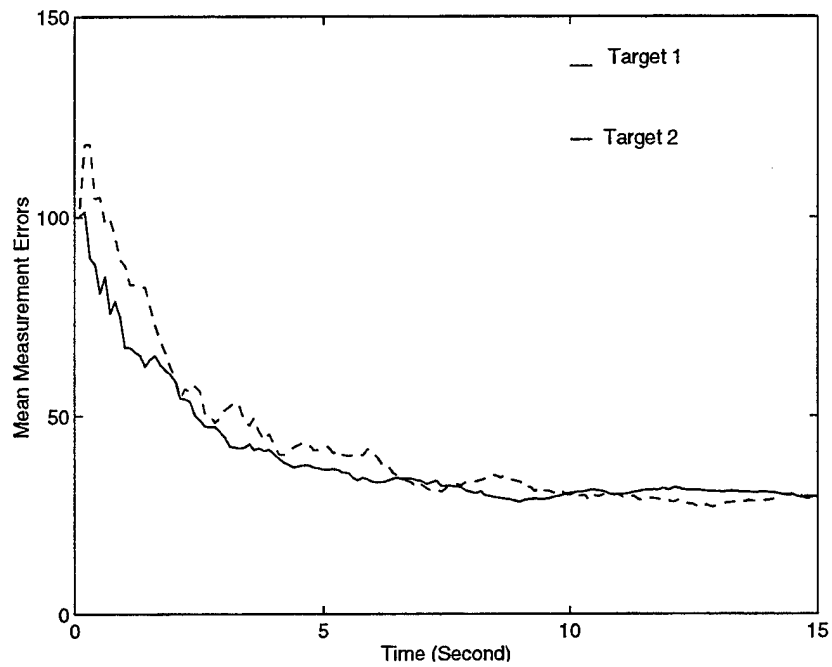


Figure 37. Mean Measurement Errors: Nearest-Neighbor Standard Filter

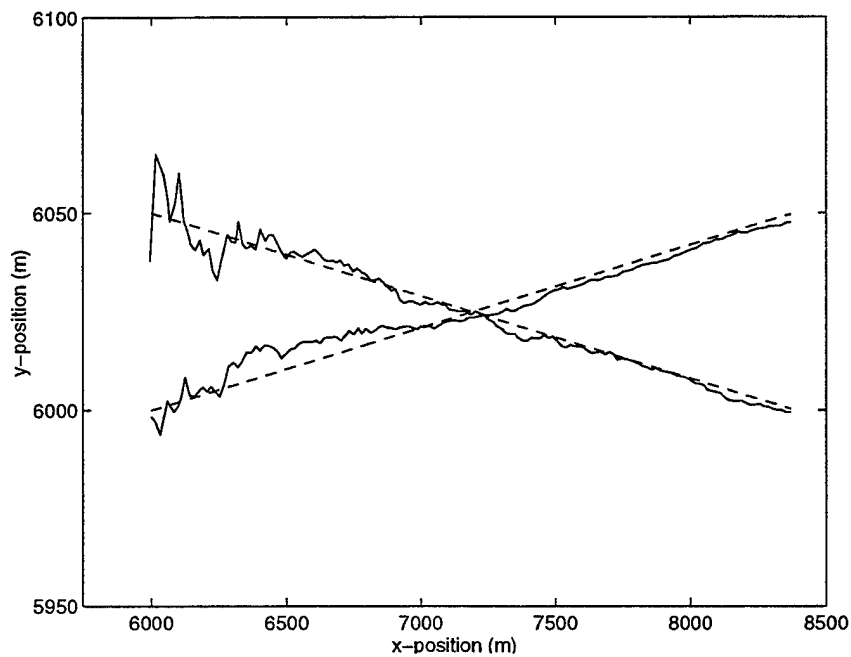


Figure 38. Actual and Mean Estimated Tracks: Perfect Data Association

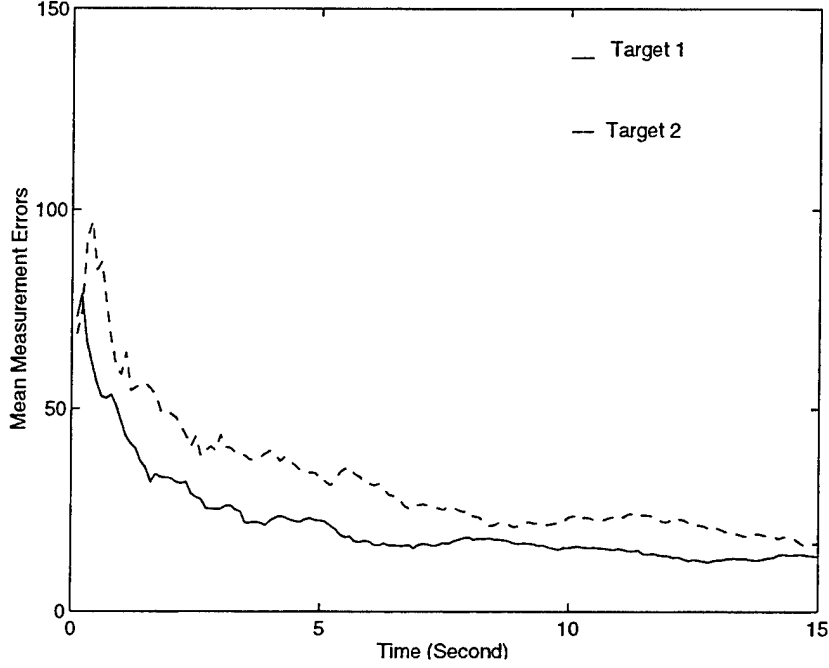


Figure 39. Mean Measurement Errors: Perfect Data Association

where the sequence $\mathbf{g}(k)$ is the plant noise with covariance \mathbf{Q} given by Equation [Ref. 84]

$$\mathbf{Q} = q^2 \begin{pmatrix} \frac{T_s^3}{3} & \frac{T_s^2}{2} & 0 & 0 \\ \frac{T_s^2}{2} & T_s & 0 & 0 \\ 0 & 0 & \frac{T_s^3}{3} & \frac{T_s^2}{2} \\ 0 & 0 & \frac{T_s^2}{2} & T_s \end{pmatrix}, \quad (\text{V.42})$$

q^2 is a scalar given by [Ref. 84, 85, 186]

$$q^2 = a^2 T_s, \quad (\text{V.43})$$

a is the acceleration, and T_s is the sampling interval.

The initial state estimates (\mathbf{x}_0) are obtained from the first two measurements by a method described by Bar-Shalom [Ref. 84]. The initial state estimate from two position measurements, $\mathbf{y}(1)$ and $\mathbf{y}(2)$, in Cartesian coordinates is given by [Ref.

$$\mathbf{x}_0 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ \frac{1}{T_s} & 0 & \frac{-1}{T_s} & 0 \\ 0 & 1 & 0 & 0 \\ 0 & \frac{1}{T_s} & 0 & \frac{-1}{T_s} \end{pmatrix} \begin{pmatrix} \mathbf{y}(2) \\ \mathbf{y}(1) \end{pmatrix}, \quad (\text{V.44})$$

with corresponding initial covariance matrix

$$\mathbf{P}_0 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ \frac{1}{T_s} & 0 & \frac{-1}{T_s} & 0 \\ 0 & 1 & 0 & 0 \\ 0 & \frac{1}{T_s} & 0 & \frac{-1}{T_s} \end{pmatrix} \begin{pmatrix} \mathbf{C}_2 & 0 \\ 0 & \mathbf{C}_1 + \mathbf{H}(\mathbf{F})^{-1} \mathbf{Q}((\mathbf{F})^{-1})' \mathbf{H}' \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 & 0 \\ \frac{1}{T_s} & 0 & \frac{-1}{T_s} & 0 \\ 0 & 1 & 0 & 0 \\ 0 & \frac{1}{T_s} & 0 & \frac{-1}{T_s} \end{pmatrix}'. \quad (\text{V.45})$$

The target motion is initially in a straight line with constant velocity. The measurements are taken every 0.1 second. After generating 250 measurements (25 seconds), the targets institute a 10 *g* right turn ($g = 9.8 \text{ m}^2/\text{sec}$) and hold the turn for 100 measurements and then return to straight line motion for an additional 250 measurements (producing 600 measurements in all). The initial target states (actual trajectories) are assumed to be

$$\mathbf{x}_{t1}(0) = \begin{pmatrix} 6000 \text{ m} \\ 100 \text{ m/sec} \\ 8000 \text{ m} \\ -170 \text{ m/sec} \end{pmatrix}, \quad (\text{V.46})$$

$$\mathbf{x}_{t2}(0) = \begin{pmatrix} 6000 \text{ m} \\ 100 \text{ m/sec} \\ 7950 \text{ m} \\ -170 \text{ m/sec} \end{pmatrix}, \quad (\text{V.47})$$

$$\mathbf{x}_{t3}(0) = \begin{pmatrix} 6000 \text{ m} \\ 100 \text{ m/sec} \\ 7900 \text{ m} \\ -170 \text{ m/sec} \end{pmatrix}. \quad (\text{V.48})$$

The measured target trajectories are the true target trajectories plus noise sequences given by the noise structure of Equation V.32 assuming that

$$\mathbf{C}_1 = \text{Cov}(\mathbf{w}_1(k)) = \begin{pmatrix} 50^2 & 0 \\ 0 & 50^2 \end{pmatrix}, \quad (\text{V.49})$$

$$\mathbf{C}_2 = \text{Cov}(\mathbf{w}_2(k)) = \begin{pmatrix} 70^2 & 0 \\ 0 & 70^2 \end{pmatrix}, \quad (\text{V.50})$$

$$\mathbf{C}_3 = \text{Cov}(\mathbf{w}_3(k)) = \begin{pmatrix} 90^2 & 0 \\ 0 & 90^2 \end{pmatrix}. \quad (\text{V.51})$$

The performance is evaluated based on a 100-run Monte Carlo simulation. The results of tracking are shown in Figures 40- 43. The actual and measured target trajectories are shown in Figure 40 and Figure 41, respectively . The estimated target tracks (solid curves) using the proposed approach (Equation V.18) along with the actual target trajectories (dashed curves) for target 1 are shown in Figure 42. The overall measurement errors for all targets are evaluated using Equation V.33 and are shown in Figure 43 for target 1. Similar results are obtained for targets 2 and 3. Table X lists the measurement errors of the proposed fuzzy approach, the nearest-neighbor standard filter, and perfect data association for different values of noise uncertainties (i.e., $\sigma_{xi} = \sigma_{yi} = \sigma$, $i = 1, 2, 3$). The results indicate the ability of the proposed algorithm to track all targets correctly. The performance of the proposed approach is superior to that of the nearest-neighbor standard filter in all cases. Also, its performance is reasonable with respect to perfect data association, which gives us the lower bound of the error [Ref. 3, 7]. The proposed fuzzy logic approach is not

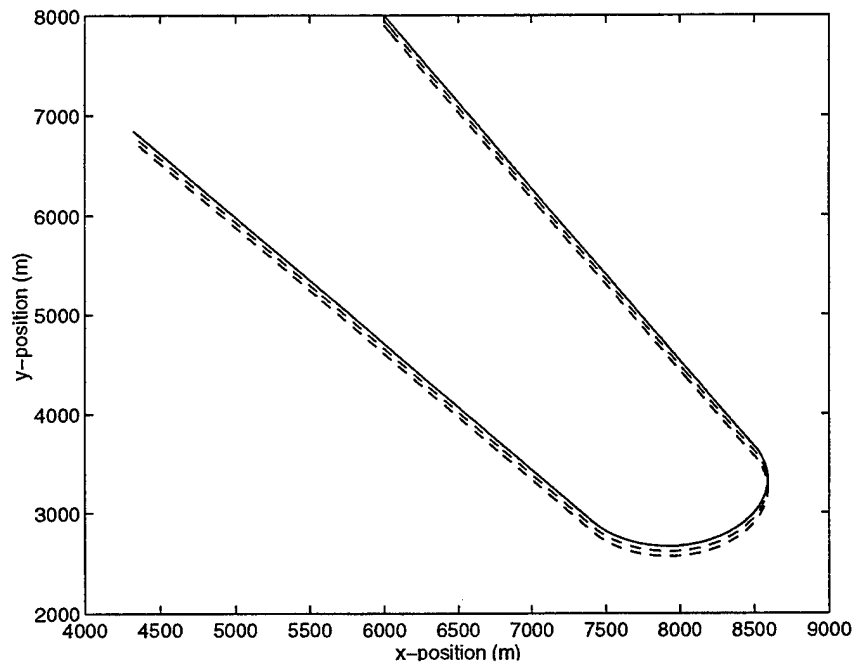


Figure 40. Actual Target Trajectories

optimal, but our objective here is to show the feasibility of using the fuzzy approach in all-neighbor data association techniques.

The problem of all-neighbor data association in multisensor-multitarget tracking systems has been considered in this chapter. A new all-neighbor fuzzy logic data association approach has been proposed. This is the first all-neighbor fuzzy data association approach developed for multisensor-multitarget tracking systems. The proposed approach incorporates all the observations within the gate of the predicted target state to update the state estimate using a membership-weighted sum of innovations. Performance has been evaluated by using Monte Carlo simulations for the cases of two crossing targets moving in straight lines and three maneuvering targets. It has been shown that the proposed approach has performed better than a comparable nearest-neighbor standard filter. Its performance with respect to perfect data association is reasonable.

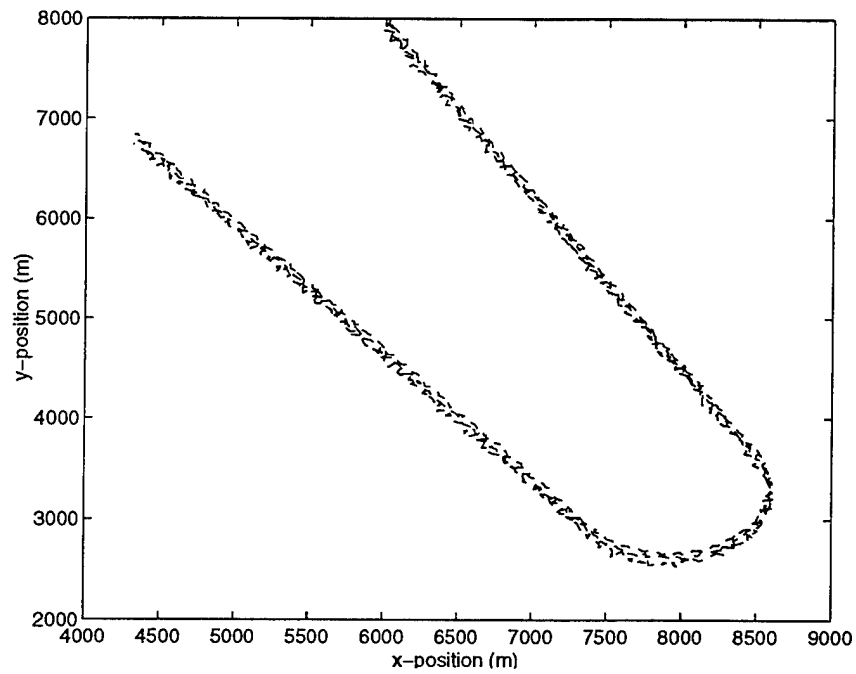


Figure 41. Measured Target Trajectories

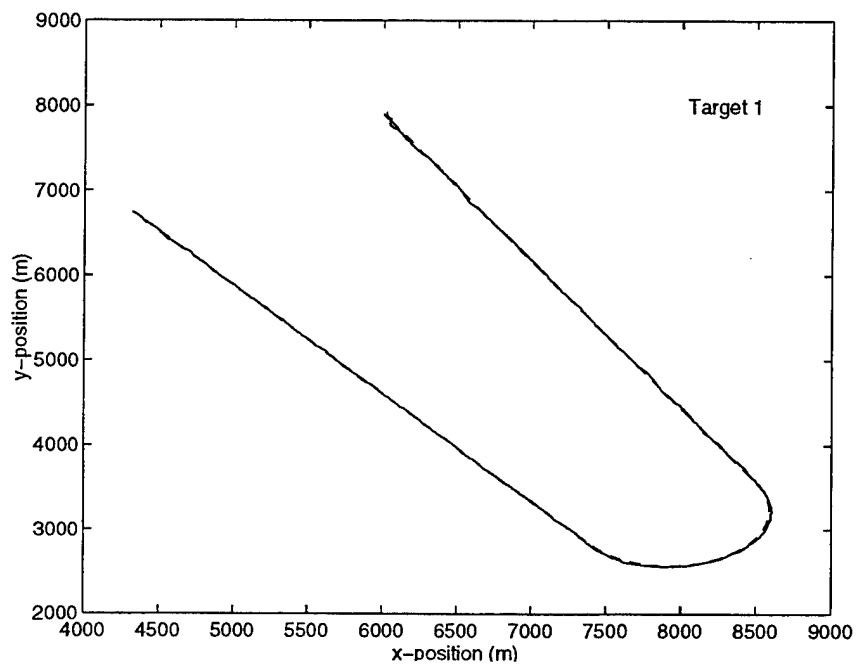


Figure 42. Actual and Mean Estimated Tracks for Target 1: Fuzzy Approach

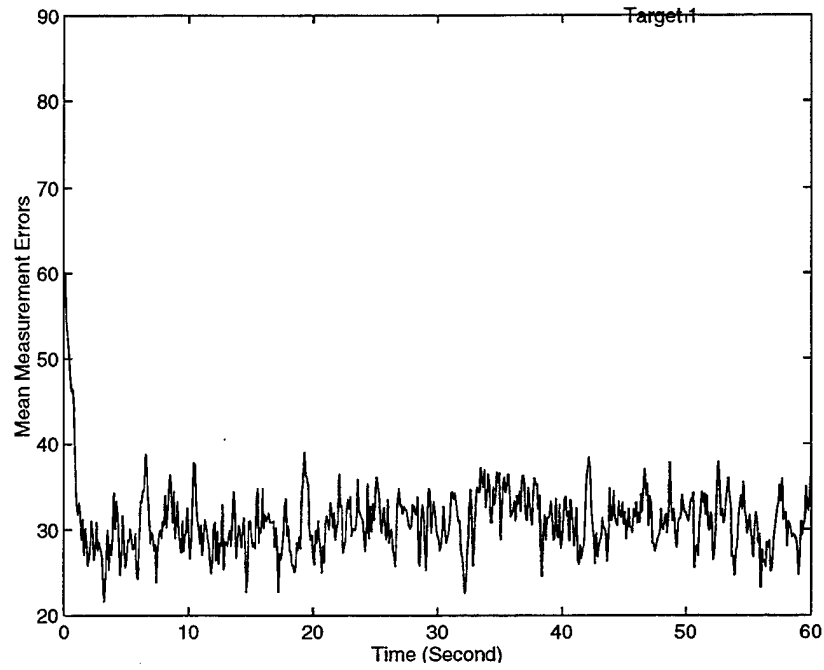


Figure 43. Mean Measurement Errors for Target 1: Fuzzy Approach

Table X. Comparison of Mean Measurement Errors

σ	All-Neighbor Fuzzy Approach	Nearest-Neighbor Standard Filter	Perfect Data Association
50	32.6	41.2	25.6
60	44.2	51.4	39.8
70	57.1	62.3	49.4
80	72.7	83.5	65.9

VI. FUZZY TRACK-TO-TRACK ASSOCIATION AND TRACK FUSION IN MULTISENSOR-MULTITARGET MULTIPLE-ATTRIBUTE ENVIRONMENT

In a multisensor-multitarget environment, where each sensor processes its own observations and sends the resultant tracks to a data fusion center, the first step is to determine whether or not two or more tracks, coming from different sensor systems with different accuracies, represent the same target (track-to-track association). The next step is to combine the sensor tracks when it is determined that they indeed represent the same target (track fusion). Both problems arise when several sensors carry out surveillance over a common volume (overlapping sensor coverage). A survey of current research in this area has been presented in Chapter III.

In this chapter, we present an efficient clustering technique to associate track information from different sensors. A superclustering technique, employing track fusion, is proposed to fuse tracks information coming from the same target. A set of fusion rules for track-to-track association are also presented, together with a new fuzzy association rule based on the concept of cross-resolution. Fuzzy track-to-track association and track fusion of tracks with different dimensionality estimates are also presented.

The proposed approaches are compared to a number of other approaches in the literature in terms of perfect data association. Application of fuzzy clustering to track association in over-the-horizon radar is also addressed. Results based on Monte Carlo simulations and real data obtained from the United States Coast Guard Vessel Traffic Services (*VTS*) system are presented. The results show that the proposed fuzzy association approaches reduce the computational complexity and improve the association performance.

A. PROPOSED TRACK-TO-TRACK ASSOCIATION AND TRACK FUSION APPROACH

1. Problem Formulation

In order to simplify our explanation, we refer to the case shown in Figure 44, where two sensors observe three targets in an overlapping coverage scenario and report four tracks to the fusion center. We assume that each reported track $R_i, i = 1, 2, 3, 4$, has two attributes, the x and y positions of the observed targets. At each scan, the data can be represented as a matrix as shown in Table XI, where columns represent tracks and rows represent attributes. The goal is to decide which tracks are similar, in the sense that they represent the same target, and when they are similar, it is required to fuse them into a single track.

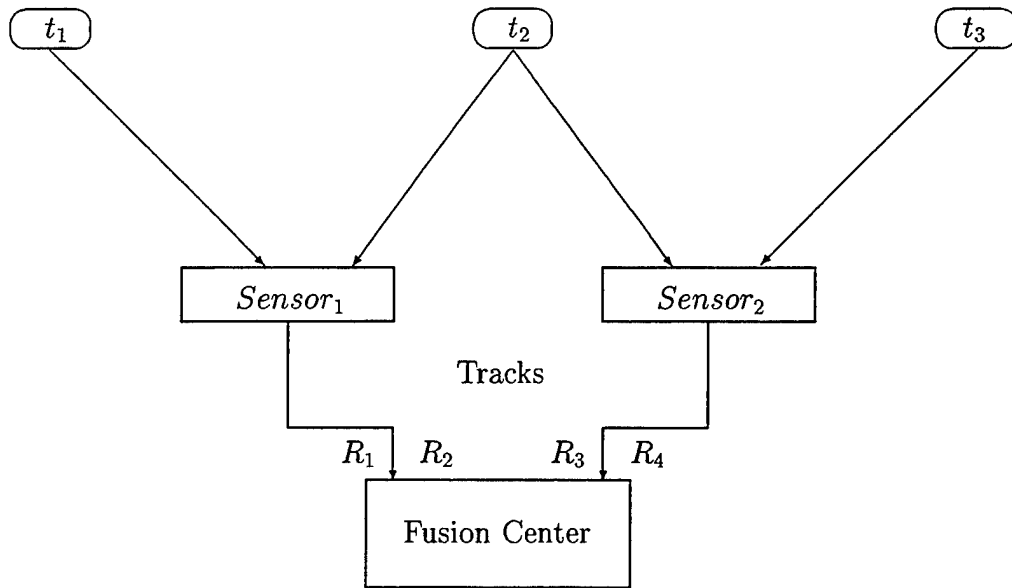


Figure 44. Multisensor-Multitarget Environment With Two Sensors and Three Targets in Overlapping Coverage Scenario

Table XI. Data Matrix

Attribute / Track	1	2	3	4
x-Position (m)	100	200	202	300
y-Position (m)	300	400	403	500

With a small data matrix like the one just shown in Table XI, we can simply look at the data matrix and find the similar and dissimilar tracks. Two tracks that have about the same values, attribute for attribute, are more similar than two tracks that do not. But for a large data matrix, visual inspection fails us and cluster analysis becomes essential. Furthermore, the number of targets is not known a priori, and an exhaustive search is not a possibility. In fact, it is well known that the number of ways of grouping n tracks into c clusters is a Stirling number of the second kind [Ref. 177] given by

$$S_n^{(c)} = \frac{1}{c!} \sum_{k=0}^{k=c} \binom{c}{k} k^n. \quad (\text{VI.1})$$

For even the relatively simple problem of sorting 25 tracks into 5 known clusters, the number of possibilities is the quantity

$$S_{25}^{(5)} \sim 2 \times 10^{14}, \quad (\text{VI.2})$$

and if the number of clusters is unknown, it becomes

$$\sum_{j=1}^{j=25} S_{25}^{(j)} > 4 \times 10^{18}. \quad (\text{VI.3})$$

The proposed track-to-track-association and track fusion approach is presented in the next section.

2. Fuzzy Track-to-Track Association

Let us assume, for simplicity, that we have two tracks coming from two different sensors

$$\mathbf{R}_i = \begin{pmatrix} \text{attribute 1} \\ \text{attribute 2} \\ \dots \\ \dots \\ \dots \\ \text{attribute } n_a \end{pmatrix}, i = 1, 2, \quad (\text{VI.4})$$

with corresponding resolutions

$$\Delta_i = \begin{pmatrix} \text{Resolution of attribute 1} \\ \text{Resolution of attribute 2} \\ \dots \\ \dots \\ \dots \\ \text{Resolution of attribute } n_a \end{pmatrix}, i = 1, 2, \quad (\text{VI.5})$$

where n_a is the total number of attributes. The first sensor (S_1) is assumed to be more accurate than the second sensor (S_2) i.e.,

$$\Delta_1(a) < \Delta_2(a) \quad \forall a = 1, 2, \dots, n_a. \quad (\text{VI.6})$$

The attributes may be range, bearing, and speed with corresponding resolutions. It is required to decide whether or not two given tracks represent the same target.

We consider this problem as a binary hypothesis testing for two local sensors. The two hypotheses are: (1) the two tracks represent the same target (H_1) and (2) the two tracks represent different targets (H_0), i.e.,

$$H = \begin{cases} 1, & H_1 \text{ the two tracks are the same} \\ 0, & H_0 \text{ the two tracks are different.} \end{cases} \quad (\text{VI.7})$$

The two-track attribute differences $|\mathbf{R}_2 - \mathbf{R}_1|$ can be compared with either the resolution of sensor 1 (Δ_1) or the resolution of sensor 2 (Δ_2). Define the comparison terms as distances

$$d_{ij} = \begin{cases} \|\mathbf{R}_j - \mathbf{R}_i\|, & \text{if } i \neq j \\ \|\Delta_i\|, & \text{if } i = j, \end{cases} \quad (\text{VI.8})$$

where $\|\cdot\|$ is an inner product induced norm. Defining d_{ij} as the Euclidean norm yields

$$d_{11} = \sqrt{\Delta_1' \Delta_1}, \quad (\text{VI.9})$$

$$d_{12} = \sqrt{(\mathbf{R}_2 - \mathbf{R}_1)' (\mathbf{R}_2 - \mathbf{R}_1)}, \quad (\text{VI.10})$$

$$d_{21} = \sqrt{(\mathbf{R}_1 - \mathbf{R}_2)' (\mathbf{R}_1 - \mathbf{R}_2)} = d_{12}, \quad (\text{VI.11})$$

$$d_{22} = \sqrt{\Delta_2' \Delta_2}. \quad (\text{VI.12})$$

The similarity measures between the elements of $\{d_{ij}\}, i = 1, 2, j = 1, 2$ can be determined as the optimum degrees of membership using the fuzzy clustering means algorithm as (see Chapter IV, Section C):

$$\mu_{ij} = \frac{(1/d_{ij})^{\frac{2}{m-1}}}{[\sum_{s=1}^c (1/d_{sj})^{\frac{2}{m-1}}]} \quad \forall i, j = 1, 2, \quad (\text{VI.13})$$

where c represents the total number of tracks ($c = 2$ in our case). Substituting from Equations VI.9- VI.12 in VI.13 yields

$$\mu_{11} = \frac{(1/\Delta_1' \Delta_1)^{\frac{1}{m-1}}}{(1/\Delta_1' \Delta_1)^{\frac{1}{m-1}} + (1/(\mathbf{R}_1 - \mathbf{R}_2)' (\mathbf{R}_1 - \mathbf{R}_2))^{\frac{1}{m-1}}}, \quad (\text{VI.14})$$

$$\mu_{12} = \frac{(1/(\mathbf{R}_1 - \mathbf{R}_2)' (\mathbf{R}_1 - \mathbf{R}_2))^{\frac{1}{m-1}}}{(1/\Delta_2' \Delta_2)^{\frac{1}{m-1}} + (1/(\mathbf{R}_2 - \mathbf{R}_1)' (\mathbf{R}_2 - \mathbf{R}_1))^{\frac{1}{m-1}}}, \quad (\text{VI.15})$$

$$\mu_{21} = \frac{(1/(\mathbf{R}_2 - \mathbf{R}_1)' (\mathbf{R}_2 - \mathbf{R}_1))^{\frac{1}{m-1}}}{(1/\Delta_1' \Delta_1)^{\frac{1}{m-1}} + (1/(\mathbf{R}_1 - \mathbf{R}_2)' (\mathbf{R}_1 - \mathbf{R}_2))^{\frac{1}{m-1}}}, \quad (\text{VI.16})$$

$$\mu_{22} = \frac{(1/\Delta_2' \Delta_2)^{\frac{1}{m-1}}}{(1/\Delta_2' \Delta_2)^{\frac{1}{m-1}} + (1/(\mathbf{R}_2 - \mathbf{R}_1)' (\mathbf{R}_2 - \mathbf{R}_1))^{\frac{1}{m-1}}}, \quad (\text{VI.17})$$

and they can be written in matrix form as

$$\mathbf{U} = \begin{pmatrix} \mu_{11} & \mu_{12} \\ \mu_{21} & \mu_{22} \end{pmatrix}. \quad (\text{VI.18})$$

In this formulation, μ_{ii} represents the degree of membership of the resolution of sensor $i, i = 1, 2$, and μ_{ij} represents the degree of membership of the difference between two tracks \mathbf{R}_i and \mathbf{R}_j with respect to the resolution of sensor j (the degree of similarity between a pair of tracks). With the diversity in the relative sensor resolutions, the global association decision (D_g) is always based on the least accurate sensor (sensor 2). In this case

$$D_g = \begin{cases} 1, & \text{if } \mu_{12} > \mu_{22} \\ 0, & \text{if } \mu_{12} < \mu_{22}. \end{cases} \quad (\text{VI.19})$$

The correlation between the two reports \mathbf{R}_1 and \mathbf{R}_2 can then be defined as:

$$CORR(1, 2) = \begin{cases} 1, & \text{if } D_g = 1 \text{ (same tracks)} \\ 0, & \text{if } D_g = 0 \text{ (different tracks)}. \end{cases} \quad (\text{VI.20})$$

In the literature, the association decision is determined by treating all the tracks in a pairwise manner. However, the previous track to track fuzzy association approach can easily be extended to the case of n_r reports obtained from more than two sensors observing multiple targets (see Figure 45). In this case, the association decision can be obtained by treating all the tracks at once or pairwise. The former case avoids the conflict situation when track A is associated with track B , track B is associated with track C , but track A is not associated with track C .

3. Fuzzy Track Fusion

Once two or more tracks have been associated to the same target, the next step is to combine them into a single track. This can be done either by adopting the superior (best) track, or by fusing the tracks into a single one. It will be shown that under certain conditions the fused track may yield a worse estimate than the superior track. In this case, track fusion is not recommended.

The superior track can be chosen according to the characteristics of the sensors in terms of sensor resolutions. If the sensors have the same resolution, the superior track is chosen according to the operating conditions such as the relative distance to the target [Ref. 75, 76, 77, 131]. The smaller relative distance the more accurate is the sensor track estimate. In our approach, the superior track is determined automatically from the data on the basis of the maximum degree of membership in the diagonal elements of the obtained similarity matrix \mathbf{U} (Equation VI.18).

If we call “ s ” the number of tracks representing the same target i , i.e., if

$$\text{CORR}(k_1, i) = \text{CORR}(k_2, i) = \dots \text{CORR}(k_s, i) = 1, \quad (\text{VI.21})$$

then the superior track is determined from the maximization

$$\mu_{k_{sup}k_{sup}} = \max_k \{\mu_{kk}\}, k = k_1, k_2, \dots, k_s, \quad (\text{VI.22})$$

and it is assigned as

$$\mathbf{R}_{sup} = \mathbf{R}_{k_{sup}}. \quad (\text{VI.23})$$

This means that the superior track is determined automatically according to the sensor resolutions as well as the relative distance to the targets.

In the case of track fusion, we can combine the tracks according to the corresponding degrees of membership. In this way, the fused track estimate can be defined as

$$R_f = \frac{\sum_{i=k_1}^{i=k_s} R_i \mu_{ii}}{\sum_{i=k_1}^{i=k_s} \mu_{ii}}. \quad (\text{VI.24})$$

The proposed fuzzy track-to-track association and track fusion approach is shown in the block diagram of Figure 45.

To explain the proposed track-to-track association and track fusion approach with the help of an example, we consider the scenario of Figure 44 given the data of Table XI. In this case, we have the following four tracks

$$\mathbf{R}_1 = \begin{pmatrix} 100 \\ 300 \end{pmatrix}, \quad (\text{VI.25})$$

$$\mathbf{R}_2 = \begin{pmatrix} 200 \\ 400 \end{pmatrix}, \quad (\text{VI.26})$$

$$\mathbf{R}_3 = \begin{pmatrix} 202 \\ 403 \end{pmatrix}, \quad (\text{VI.27})$$

$$\mathbf{R}_4 = \begin{pmatrix} 300 \\ 500 \end{pmatrix}. \quad (\text{VI.28})$$

We assume the sensor resolutions

$$\Delta_1 = \begin{pmatrix} 10 \\ 15 \end{pmatrix}, \quad (\text{VI.29})$$

$$\Delta_2 = \begin{pmatrix} 20 \\ 30 \end{pmatrix}. \quad (\text{VI.30})$$

Given these data, we obtain the distance measures using Equations VI.9- VI.12 , assuming $m = 2$, in matrix form as

$$\mathbf{D} = \begin{pmatrix} d_{11} & d_{12} & d_{13} & d_{14} \\ d_{21} & d_{22} & d_{23} & d_{24} \\ d_{31} & d_{32} & d_{33} & d_{34} \\ d_{41} & d_{42} & d_{43} & d_{44} \end{pmatrix} = \begin{pmatrix} 18.0 & 141.4 & 144.9 & 282.8 \\ 141.4 & 18.0 & 3.6 & 141.4 \\ 144.9 & 3.6 & 36.1 & 137.9 \\ 282.8 & 141.4 & 137.9 & 36.1 \end{pmatrix}. \quad (\text{VI.31})$$

The similarity measures as the optimum degrees of membership are obtained using VI.13 in matrix form as

$$\mathbf{U} = \begin{pmatrix} \mu_{11} & \mu_{12} & \mu_{13} & \mu_{14} \\ \mu_{21} & \mu_{22} & \mu_{23} & \mu_{24} \\ \mu_{31} & \mu_{32} & \mu_{33} & \mu_{34} \\ \mu_{41} & \mu_{42} & \mu_{43} & \mu_{44} \end{pmatrix} = \begin{pmatrix} 0.9655 & 0.0006 & 0.0006 & 0.0141 \\ 0.0157 & 0.0384 & 0.9888 & 0.0565 \\ 0.0149 & 0.9603 & 0.0099 & 0.0595 \\ 0.0039 & 0.0006 & 0.0007 & 0.8698 \end{pmatrix}. \quad (\text{VI.32})$$

Applying the association rule of Equation VI.19 yields the correlation matrix

$$\mathbf{CORR} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}. \quad (\text{VI.33})$$

Since $\mathbf{CORR}(i, j) = 0, j = 1, 4, \forall i \neq j$, then tracks 1 and 4 represent independent targets. Since $\mathbf{CORR}(3, 2) = \mathbf{CORR}(2, 3) = 1$, then tracks 2 and 3 represent the same target. When it is decided that tracks 2 and 3 coming from the same target (since $\mu_{22} > \mu_{33}$), we can adopt the superior track according to Equation VI.23 as:

$$\mathbf{R}_{sup} = \mathbf{R}_2, \quad (\text{VI.34})$$

or fuse both tracks according to Equation VI.24 as

$$R_f = \frac{\mathbf{R}_2\mu_{22} + \mathbf{R}_3\mu_{33}}{\mu_{22} + \mu_{33}}. \quad (\text{VI.35})$$

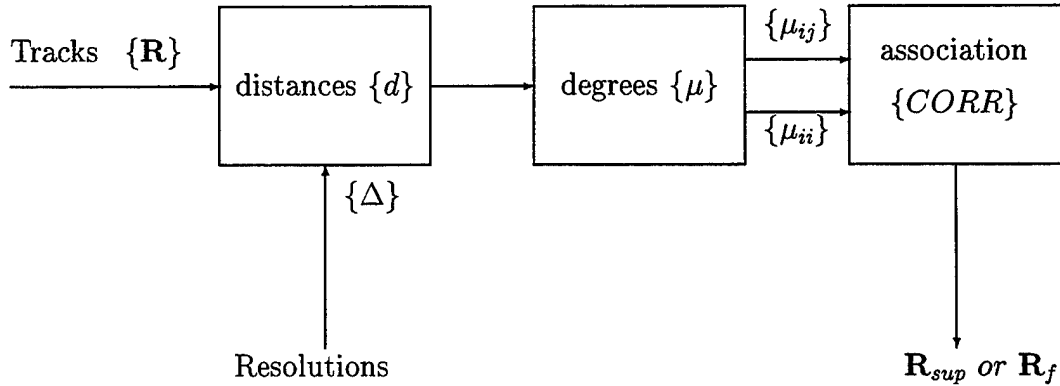


Figure 45. Proposed Fuzzy Track-to-Track Association and Track Fusion Approach

B. NUMERICAL RESULTS

Two examples are considered to evaluate the performance of the proposed clustering approach. The first example considers the case of four emitters with different radio frequencies (RF) and pulse repetition intervals (PRI) [Ref. 74]. Figure 46 depicts the four basic data points ($RF_{i0}, PRI_{i0}, i = 1, 2, 3, 4$) where 0 denotes the original values of RF and PRI in a clear environment (unknown values). The separation between the four data points is labeled “ w ”. The measured RF and PRI are the original values plus noise. The noise in both RF and PRI directions is assumed to be a zero mean Gaussian noise with a common standard deviation σ . Figures 47 and 48 show the scenario assuming that only one parameter is fixed and the other parameter is changing randomly for small and large values of σ respectively. The resolution of each emitter is represented as

$$\Delta_i = \begin{pmatrix} 3 \sigma_{RF_i} \\ 3 \sigma_{PRI_i} \end{pmatrix}, i = 1, 2, 3, 4, \quad (\text{VI.36})$$

where $\sigma_{RF_i} = \sigma_{PRI_i} = \sigma$.

The objective is to determine the right number of clusters (4 emitters in our example). The performance is measured in terms of correctly clustering the data points into 4 clusters for different values of w/σ . We process 100 samples, i.e., four hundred data points, over 1000 Monte Carlo simulations. Figure 49 compares the performance of the proposed clustering approach with the performance of the Euclidean clustering [Ref. 90, 177]. The percentage of correct clustering using the Euclidean approach varies from 57.4% to 99.2%, while it varies from 79.2% to 99.9% using the proposed clustering approach. The performance of the proposed clustering approach is always better than the performance of the Euclidean clustering for all values of w/σ . For large σ ($w/\sigma=0.25$), the performance of the proposed clustering approach is 79.2% as opposed to 57.4% in the Euclidean case. The results show that the proposed clustering approach is much more efficient than the Euclidean clustering. In this example, the proposed approach achieves as much as 22% performance improve-

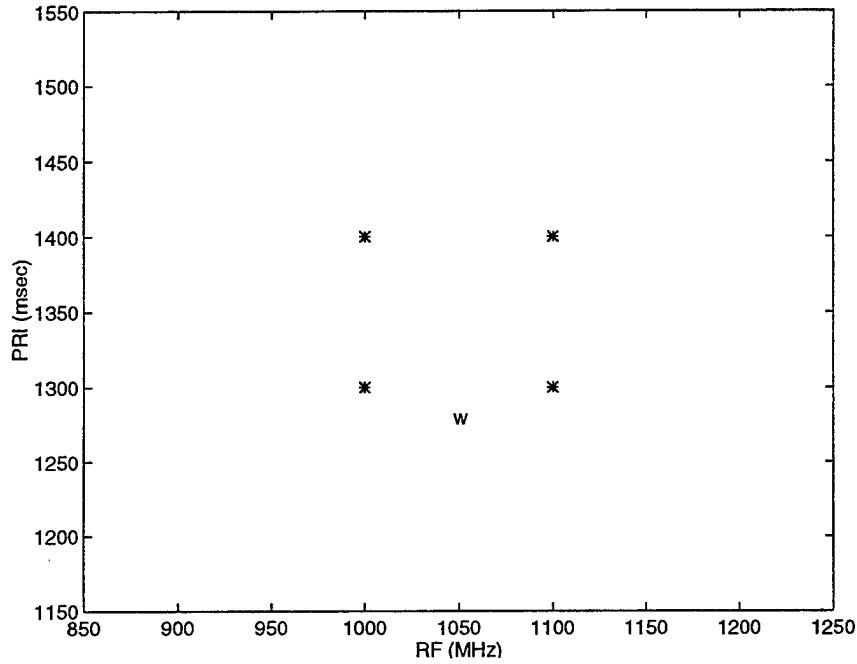


Figure 46. Initial Values of RF and PRI for Clustering Analysis

ment as opposed to 15% in case of using the proposed fuzzy approach of Smith [Ref. 74] in the same simulated example.

Figures 50 and 51 show the same scenario in case of random values in both RF and PRI directions. In this case, the clustering problem is more complicated. Figure 52 shows the performance in terms of the percentage of correct clustering. The percentage of correct clustering using the Euclidean approach varies from 35% to 99.4%, while it varies from 64.85% to 99.8% using the proposed clustering approach. As shown in Figure 52, the fuzzy clustering is always superior to the Euclidean clustering.

In the second example, we consider the case of four targets ($n_t = 4$), moving in straight lines, observed by five sensors ($n_s = 5$) in overlapping coverage scenario. This scenario is depicted in Figure 53, where: 1) target 1 is only detected by sensor 1 and target 4 is only detected by sensor 5 (sensors observe only one target), 2) target 2 is detected by sensor 2 and sensor 3, and target 4 is detected by sensor 4 and sensor 5 (targets are detected by two sensors), 3) target 3 is detected by sensor 2, sensor 3

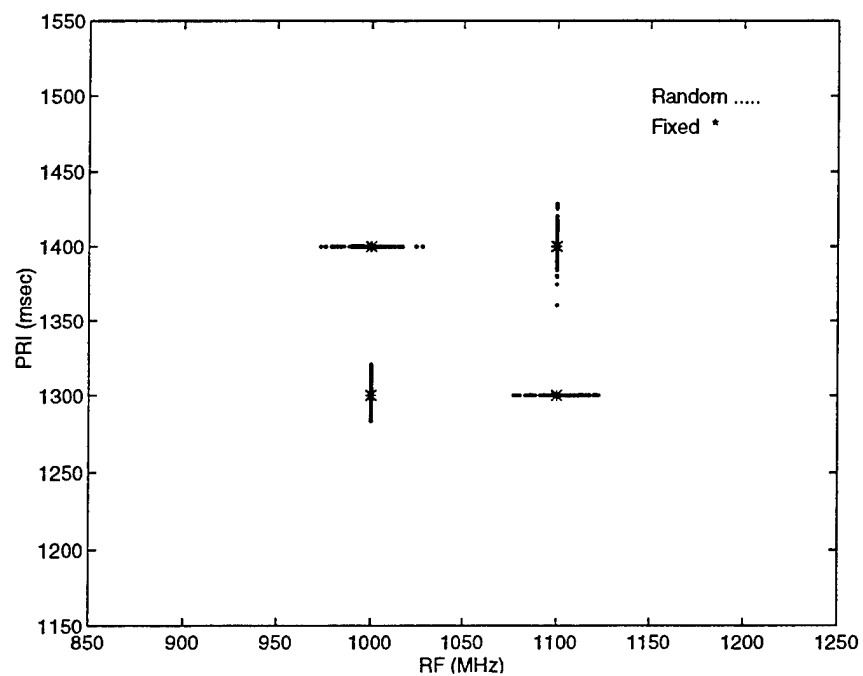


Figure 47. Random Data Along Fixed Directions for Small Noise Standard Deviation

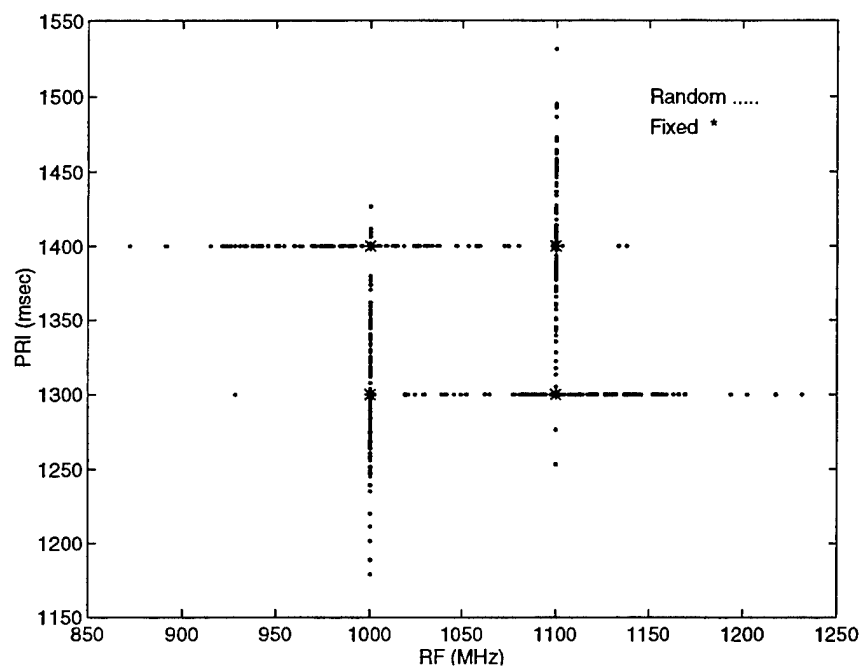


Figure 48. Random Data Along Fixed Directions for Large Noise Standard Deviation

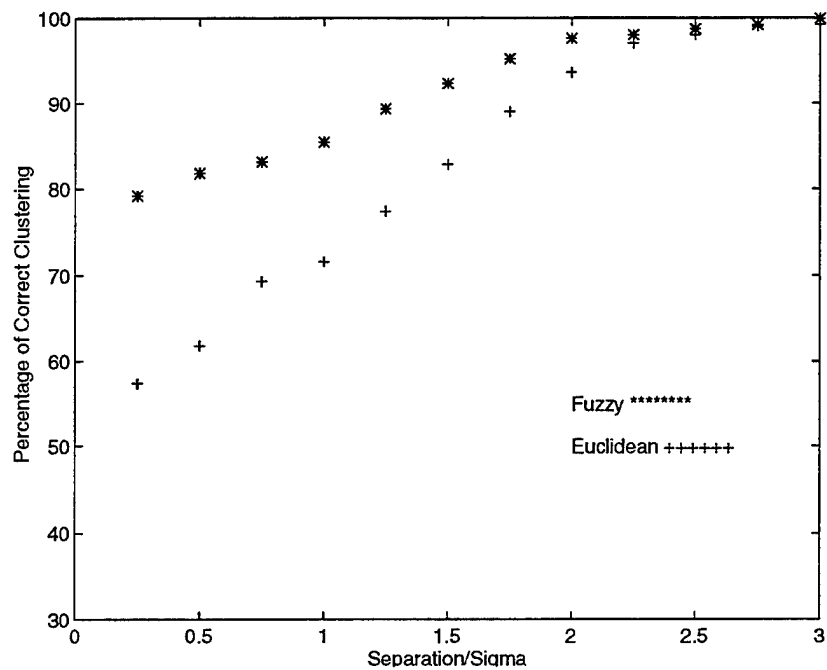


Figure 49. Comparison of Fuzzy and Euclidean Clustering

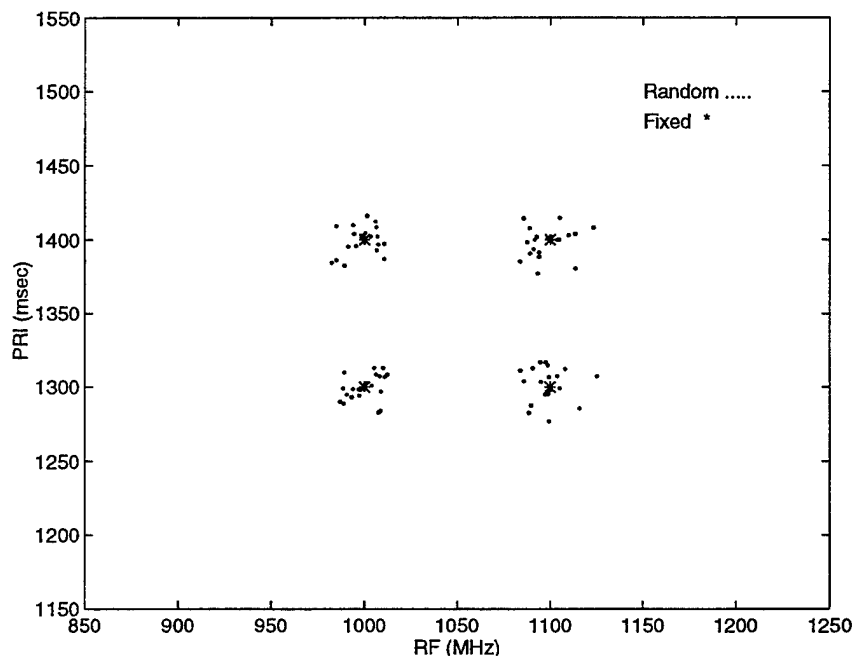


Figure 50. Random Data of Both RF and PRI for Small Noise Standard Deviation

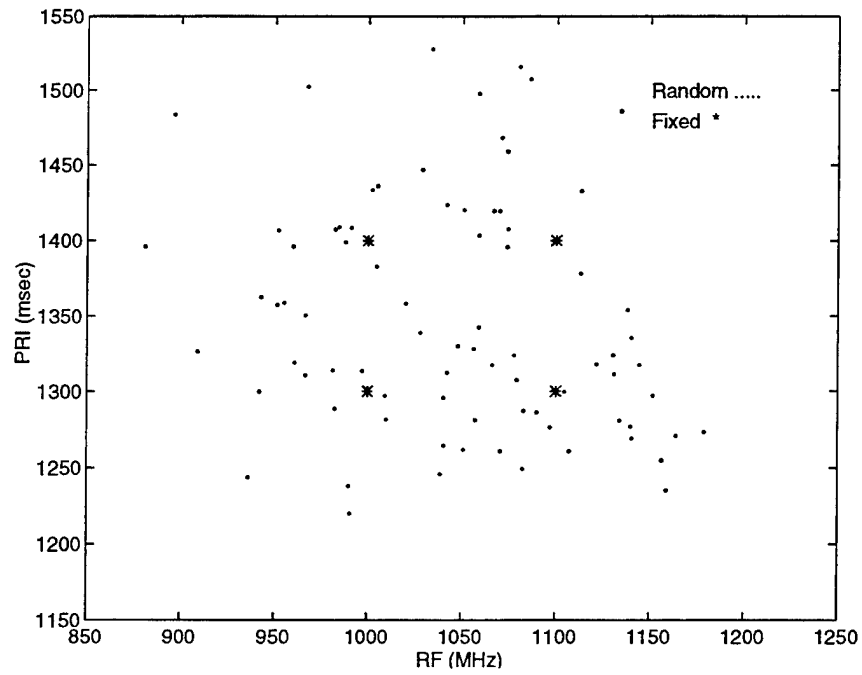


Figure 51. Random Data of Both RF and PRI for Large Noise Standard Deviation

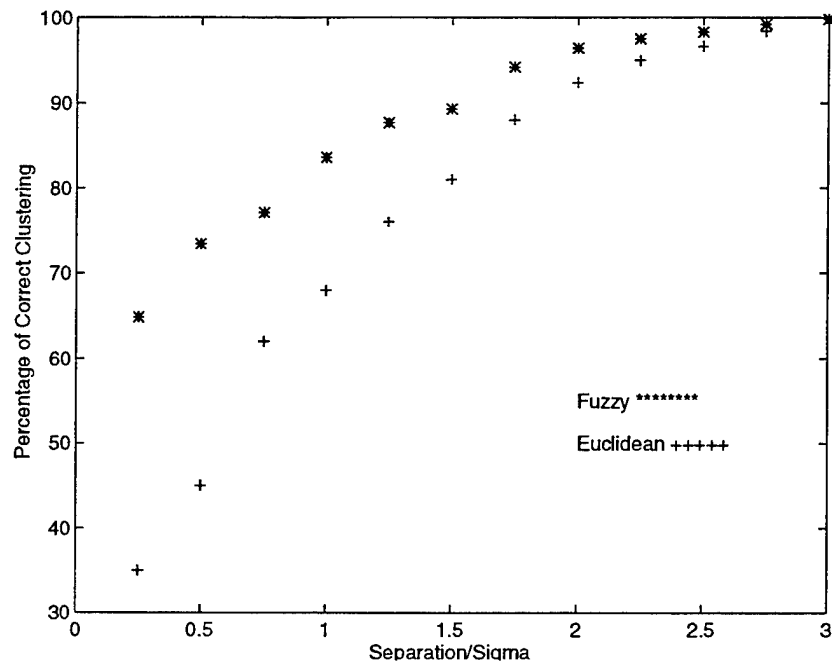


Figure 52. Comparison of Fuzzy and Euclidean Clustering

and sensor 4 (a target is detected by three sensors), and 4) sensor 2 observes target 2 and target 3, and sensor 4 observes target 3 and target 4 (sensors detect two targets).

The five sensors send eight reports $\{R_{ij}\}$ to the data fusion center, where R_{ij} represents the report from sensor j due to observing target i . Each report represents the x and y positions of the targets ($n_a = 2$). Measurements are affected by noise which is modeled as Gaussian, zero mean, with a given standard deviation for each scan k . The noise sequence has a covariance matrix

$$\mathbf{C}_{jk} = \text{Cov}(\mathbf{w}(k)) = \begin{pmatrix} \sigma_{ij}^2 & 0 \\ 0 & \sigma_{ij}^2 \end{pmatrix}, \quad (\text{VI.37})$$

where σ_{ij}^2 represents the variance of the measurements error due to observing target i by sensor j . The values of noise uncertainties (in meters) are taken as $\sigma_{11} = 25$, $\sigma_{22} = 30$, $\sigma_{32} = 30$, $\sigma_{23} = 40$, $\sigma_{33} = 40$, $\sigma_{34} = 45$, $\sigma_{44} = 45$, and $\sigma_{45} = 50$.

The fusion center is responsible for processing all of the reported tracks and fusing the redundant tracks into a single set of tracks. The actual target trajectories are shown in Figure 54. The displayed tracks before and after fusion are shown in Figure 55 and Figure 56, respectively. The proposed clustering approach successfully associates all the reported tracks and displays the right number of reports n_{rf} , under all considered situations, where n_{rf} represents the number of displayed tracks after fusion. All the redundant tracks are fused and all the superior tracks are correctly determined. Typical numerical results of the reported tracks (meters), sensor resolutions (meters), grades of membership, correlation matrix, and the priorities of the superior tracks are shown in Tables XII - XVI, for a given scan k .

The performance of the fused track is also compared to that of the superior track for the scenario of target 3 in Figure 53. Target 3 is detected by three different sensors, sensor 2, sensor 3, and sensor 4. Three tracks, representing target 3, are reported to the data fusion center, which are \mathbf{R}_{32} , \mathbf{R}_{33} , and \mathbf{R}_{34} . The data fusion center can either adopt the superior of the three reported tracks (Equation VI.23) or

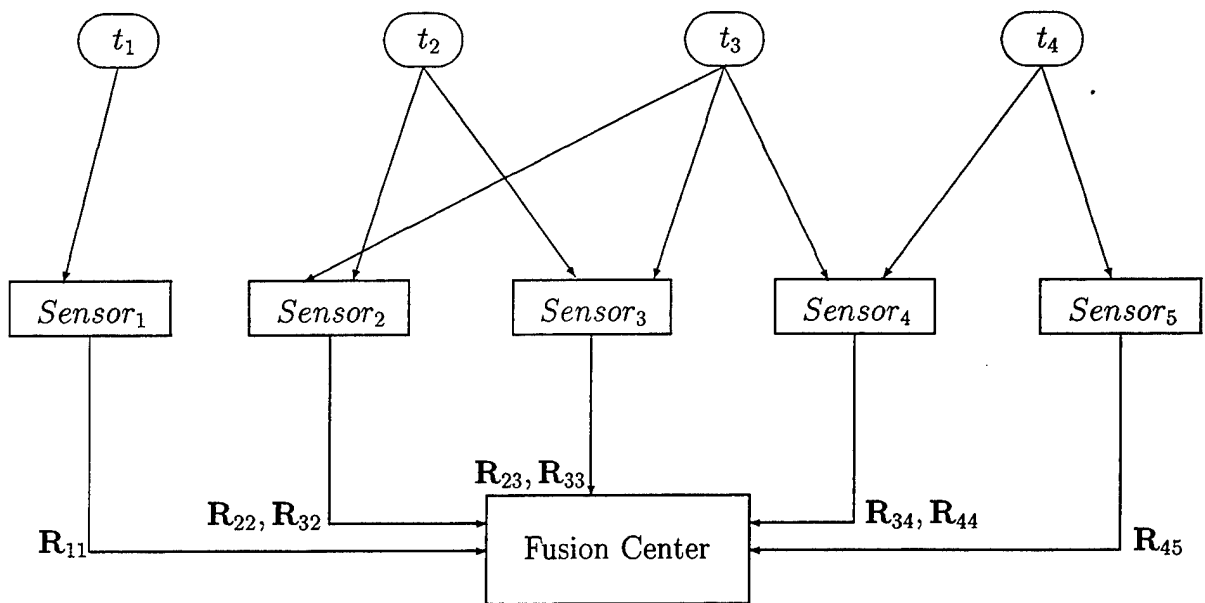


Figure 53. Four Targets and Five Sensors in Overlapping Coverage Scenario

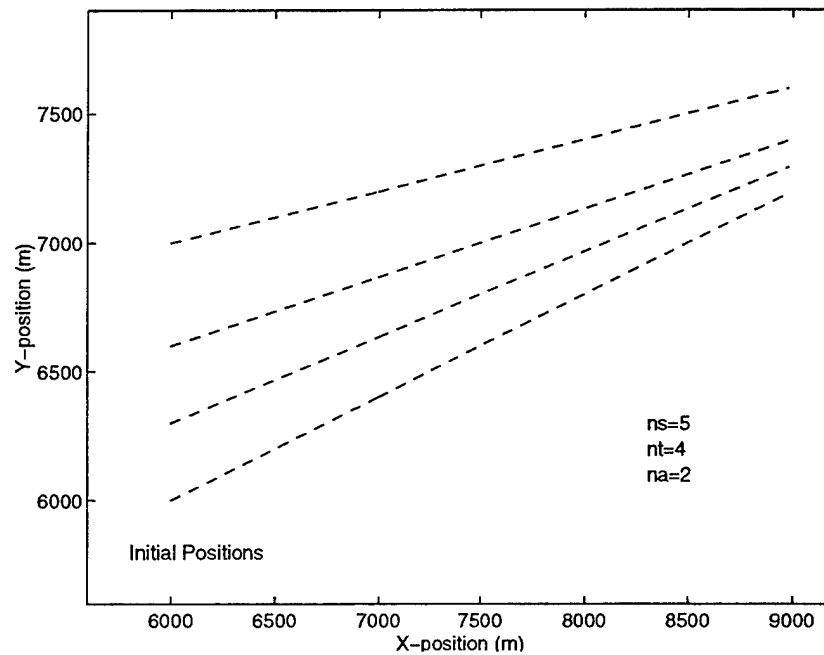


Figure 54. Actual Target Trajectories

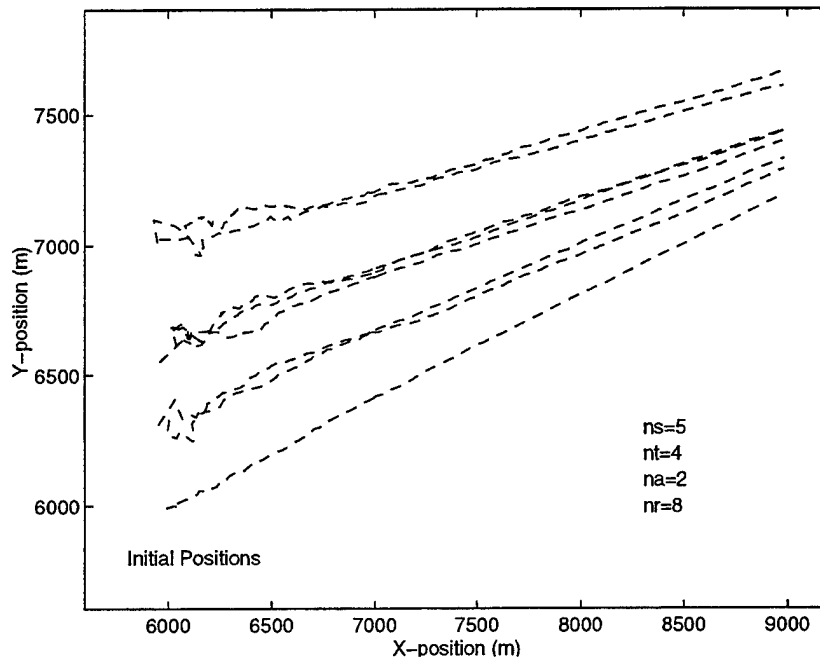


Figure 55. Displayed Tracks Before Fusion

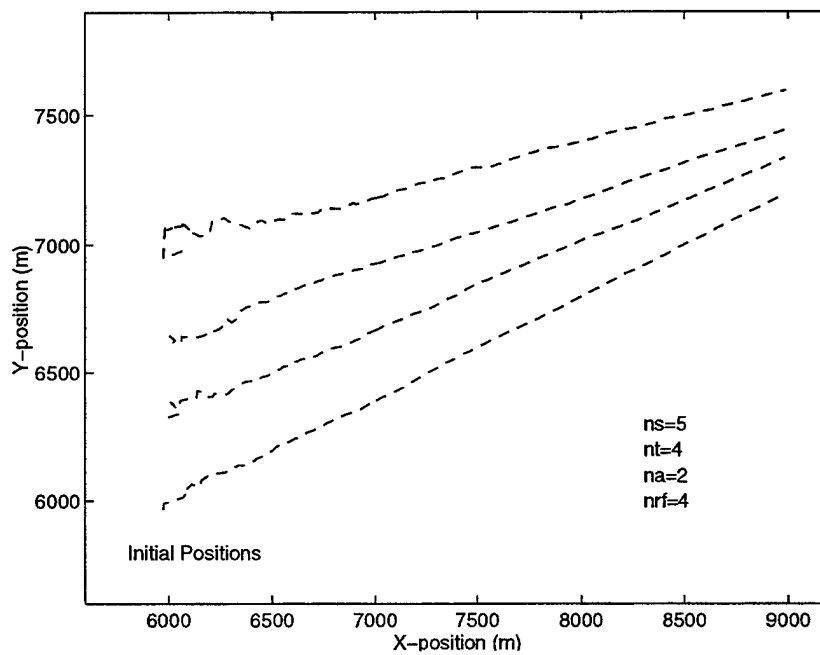


Figure 56. Displayed Tracks After Fusion

Table XII. Reported Tracks for a Given Scan k

Attribute / Report	R_{11}	R_{22}	R_{32}	R_{23}	R_{33}	R_{34}	R_{44}	R_{45}
x-Position	6019	6051	6001	6022	5963	5990	5906	6074
y-Position	5993	6257	6583	6328	6577	6531	6914	6989

Table XIII. Sensor Resolutions

Resolution / Sensor	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5
x-Resolution	75	90	120	135	150
y-Resolution	75	90	120	135	150

fuse them into a global estimate. The fused track is defined from Equation VI.24 as

$$\mathbf{R}_f = \frac{\mathbf{R}_{32} \mu_{33} + \mathbf{R}_{33} \mu_{55} + \mathbf{R}_{34} \mu_{66}}{\mu_{33} + \mu_{55} + \mu_{66}}. \quad (\text{VI.38})$$

The sensor resolutions are defined in terms of the noise standard deviation for each sensor assuming a common standard deviation in both x and y positions, i.e.,

$$\sigma_{x_i} = \sigma_{y_i} = \sigma_i, i = 2, 3, 4. \quad (\text{VI.39})$$

The performance of the superior track and the fused track are compared in terms of the mean measurement errors for different values of sensor resolutions. The results are depicted in Figures 57- 60. The results show that the performance of the fused track may perform worse than the performance of the superior track. As shown in

Table XIV. Grades of Membership

	1	2	3	4	5	6	7	8
1	0.7206	0.0574	0.0044	0.0374	0.0041	0.0049	0.0134	0.0138
2	0.1147	0.3507	0.0144	0.5657	0.0127	0.0179	0.0256	0.0256
3	0.0233	0.0380	0.0950	0.0637	0.3893	0.3790	0.0940	0.0819
4	0.0724	0.4487	0.0234	0.1454	0.0220	0.0339	0.0328	0.0310
5	0.0236	0.0370	0.4287	0.0659	0.0485	0.5097	0.0988	0.0752
6	0.0279	0.0515	0.4124	0.1005	0.5037	0.0388	0.0754	0.0633
7	0.0094	0.0090	0.0125	0.0119	0.0119	0.0092	0.3177	0.4049
8	0.0082	0.0076	0.0092	0.0095	0.0077	0.0065	0.3424	0.3043

Figures 57 and 58, the performance of the fused track is better than the performance of the superior track when the sensors have similar or comparable resolutions. As shown in Figure 57, the best performance of the fused track occurs when the sensors have the same resolutions. Figures 59 and 60 show that the performance of the fused track is worse than the performance of the superior track when the sensor resolutions vary widely. In this case, fusion of sensor tracks is not recommended and adopting the superior track is recommended. These results match the results of the classical techniques [Ref. 119, 143, 149, 150, 152, 153, 154].

C. POSSIBLE FUSION RULES FOR TRACK-TO-TRACK ASSOCIATION

Track-to-track association decision can be determined based either on the best sensor resolution or the worst sensor resolution. In the literature, either in the classical

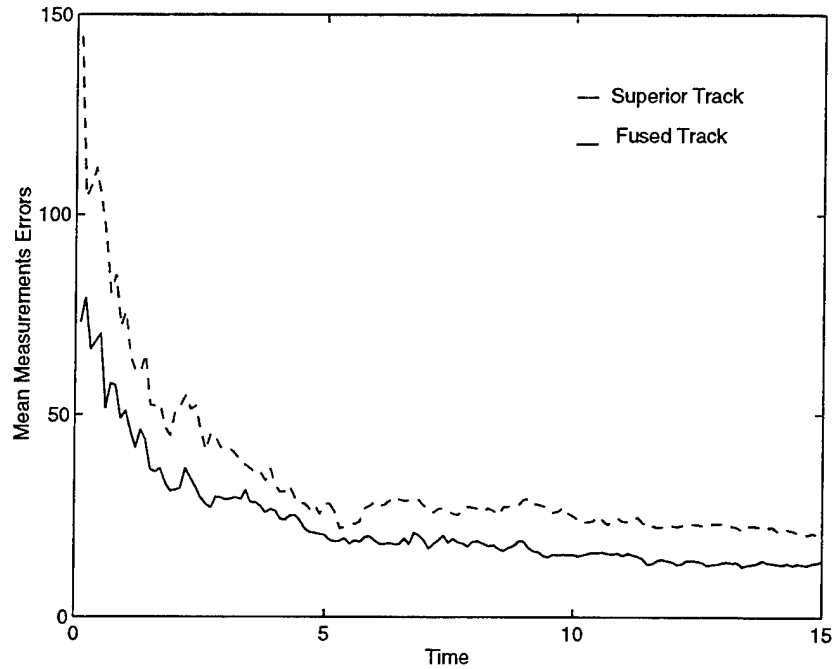


Figure 57. Comparison of Fused and Superior Track in Case of Same Sensor Resolutions, $\sigma_2 = \sigma_3 = \sigma_4 = 100\text{ m}$

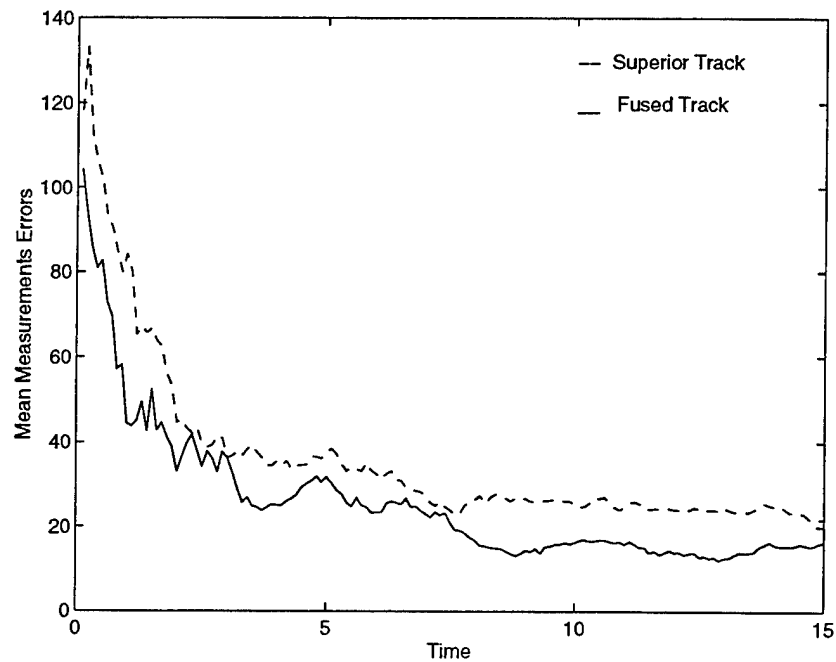


Figure 58. Comparison of Fused and Superior Track in Case of Comparable Sensor Resolutions, $\sigma_2 = 100\text{ m}$, $\sigma_3 = 120\text{ m}$, $\sigma_4 = 140\text{ m}$

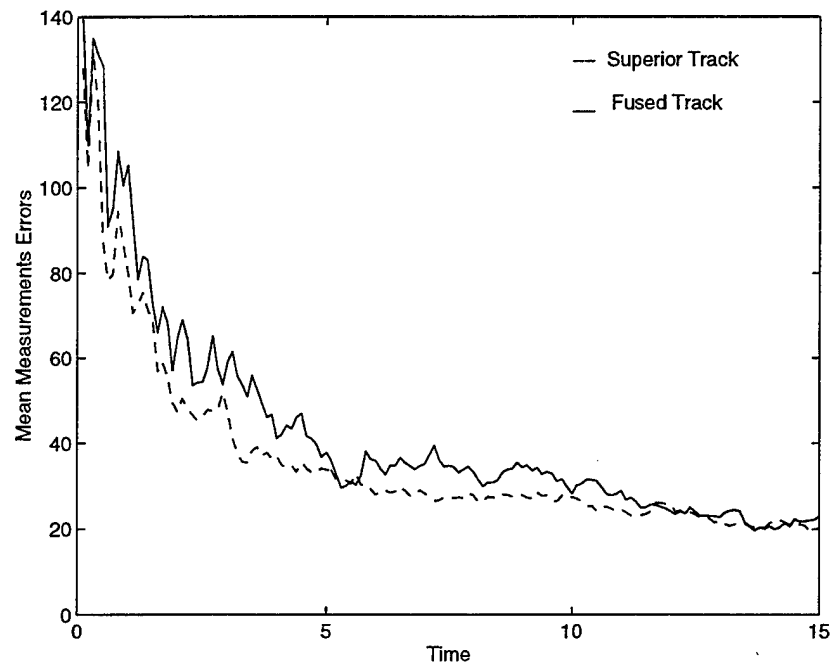


Figure 59. Comparison of Fused and Superior Track in Case of Large Differences in Sensor Resolutions, $\sigma_2 = 100\text{ m}$, $\sigma_3 = 200\text{ m}$, $\sigma_4 = 300\text{ m}$

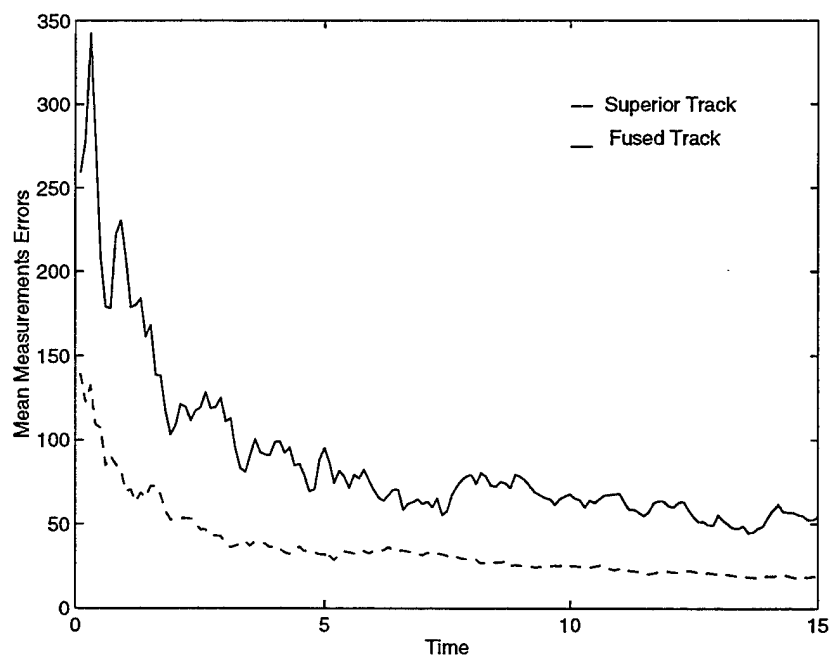


Figure 60. Comparison of Fused and Superior Track in Case of Very Large Differences in Sensor Resolutions, $\sigma_2 = 100\text{ m}$, $\sigma_3 = 500\text{ m}$, $\sigma_4 = 900\text{ m}$

Table XV. Correlation Matrix

	1	2	3	4	5	6	7	8
1	0	0	0	0	0	0	0	0
2	0	0	0	1	0	0	0	0
3	0	0	0	0	1	1	0	0
4	0	1	0	0	0	0	0	0
5	0	0	1	0	0	1	0	0
6	0	0	1	0	1	0	0	0
7	0	0	0	0	0	0	0	1
8	0	0	0	0	0	0	1	0

association techniques [Ref. 112, 113, 114] or in the fuzzy association techniques [Ref. 75, 76, 77, 131], the track-to-track association is always based on the least accurate sensor. However, the performance of track association can be improved by utilizing the fusion of different association decisions based on individual sensor resolutions.

In the case we have two sensors, i and j with different resolutions Δ_i and Δ_j with sensor i being more accurate, i.e.,

$$\Delta_i(k) < \Delta_j(k) \quad \forall k = 1, 2, \dots, n_a, \quad (\text{VI.40})$$

Table XVI. Priorities of Superior Tracks (in Case of Same Tracks)

1	2	7	8	4	3	5	6
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Table XVII. Possible Association Fusion Rules Under Hypothesis H_1

Hypothesis	D_i	D_j	$ADOPT\ i$	$ADOPT\ j$	OR	AND
H_1	0	0	0	0	0	0
H_1	0	1	0	1	1	0
H_1	1	0	1	0	1	0
H_1	1	1	1	1	1	1

fuzzy track-to-track association based on individual sensor resolutions can be obtained using Equation VI.19 as

$$D_i = \begin{cases} 1, & \text{if } \mu_{ji} > \mu_{ii} \\ 0, & \text{if } \mu_{ji} < \mu_{ii}, \end{cases} \quad (\text{VI.41})$$

$$D_j = \begin{cases} 1, & \text{if } \mu_{ij} > \mu_{jj} \\ 0, & \text{if } \mu_{ij} < \mu_{jj}, \end{cases} \quad (\text{VI.42})$$

where D_i and D_j are the association decisions based on the resolutions Δ_i and Δ_j respectively. Both association decisions can be combined at the data fusion center. The possible fusion rules for combining the binary association decisions are $ADOPT\ i$, $ADOPT\ j$, OR , and AND fusion rules. The $ADOPT\ i$ and $ADOPT\ j$ fusion rules adopt the association decision based on the best or the worst sensor resolution. The OR fusion rule favors hypothesis H_1 (decides that two tracks represent the same target) when either D_i or D_j favor hypothesis H_1 . The AND fusion rule favors hypothesis H_1 when both D_i and D_j favor hypothesis H_1 . All possible association fusion rules are shown in Tables XVIII and XVII under hypothesis H_1 and H_0 , respectively.

Table XVIII. Possible Association Fusion Rules Under Hypothesis H_0

Hypothesis	D_i	D_j	$ADOPT\ i$	$ADOPT\ j$	OR	AND
H_0	0	0	0	0	0	0
H_0	0	1	0	1	1	0
H_0	1	0	1	0	1	0
H_0	1	1	1	1	1	1

The performance of all possible fusion rules are compared in two different examples. The first example considers the case of two sensors observing one target, as shown in Figure 61, where the true hypothesis is H_1 . Each sensor track consists of two attributes, the x - and y - positions with common noise standard deviation $\sigma_i, i = 1, 2$. The average noise standard deviation is defined as

$$\sigma = \frac{\sigma_1 + \sigma_2}{2}. \quad (VI.43)$$

The sensor resolutions are adopted as three times the standard deviation. Figure 62 shows the actual target trajectories. Figures 63 and 64 show the displayed tracks before and after fusion respectively in case of 20 *meters* noise standard deviation. Figure 65 compares the performance of $ADOPT\ 1$, $ADOPT\ 2$, OR and AND fusion rules, in terms of the percentage of perfect data association, for different values of $1/\sigma$. The results show that the OR fusion rule is superior under hypothesis H_1 .

The second example considers the case of two closing targets observed by two sensors as shown in Figure 66. Each target is observed by a different sensor (the true hypothesis is H_0). Figures 67 - 70 show the same plots of the first examples assuming

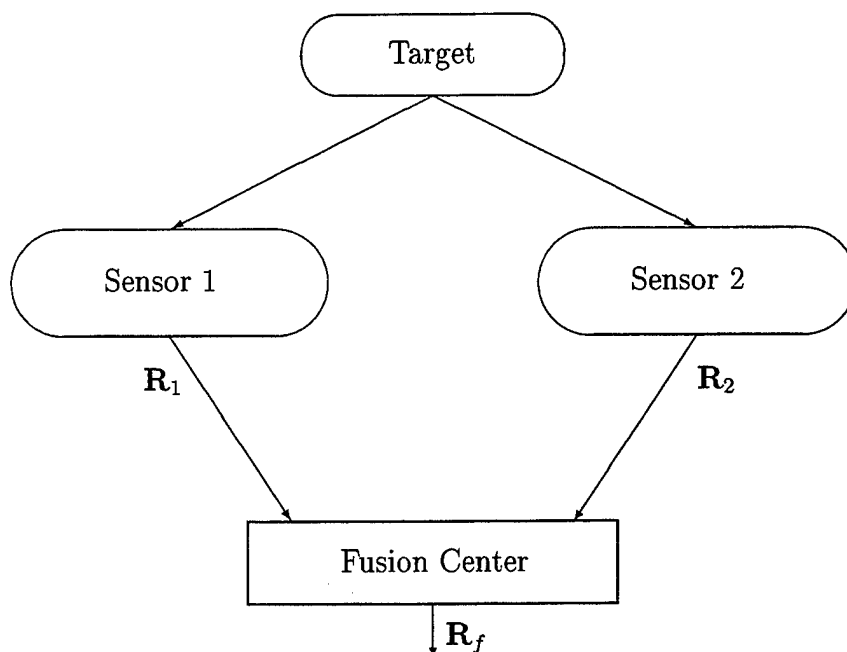


Figure 61. Two Sensors Observing One Target in Overlapping Coverage Scenario (H_1)

20 m noise standard deviation. The results in terms of perfect data association are shown in Figure 70. As shown in Figure 70, the *AND* fusion rule is superior under hypothesis H_0 . Both examples show that the fusion of association decisions improves the performance of track-to-track association.

D. NEW ASSOCIATION RULE BASED ON THE CROSS-RESOLUTION

1. Definition of the Cross-Resolution

As mentioned in the previous section, the *OR* fusion rule is superior under hypothesis H_1 while the *AND* fusion rule is superior under hypothesis H_0 . The choice between them depends on the application. Since the true hypothesis is not known *a priori*, a new association rule is proposed to overcome this problem. The proposed association rule depends on the concept of the cross-resolution between two sensors i and j . The classical techniques of data association utilize the cross-covariance between two sensor estimates to improve the performance of track-to-track association. Given

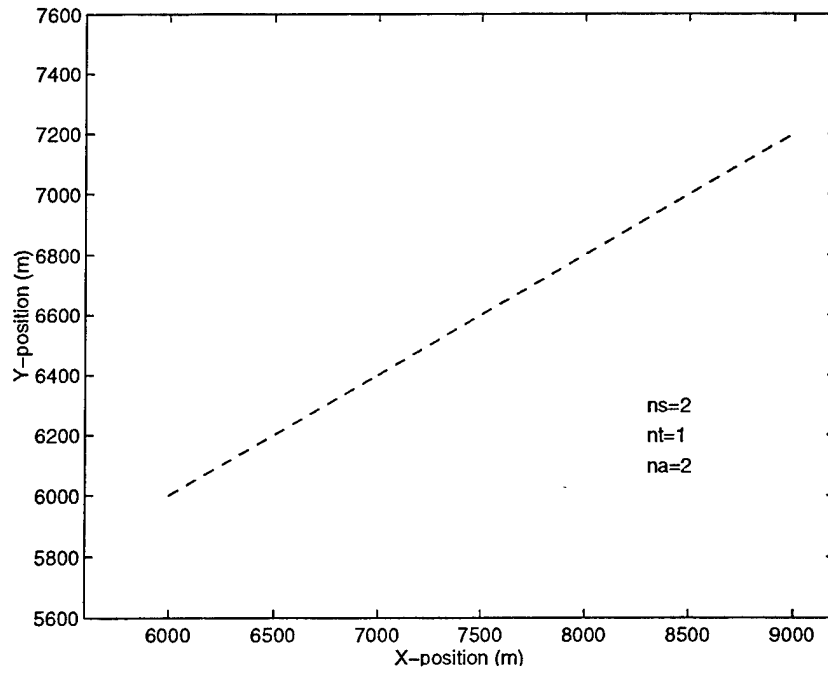


Figure 62. Actual Target Trajectory (H_1)

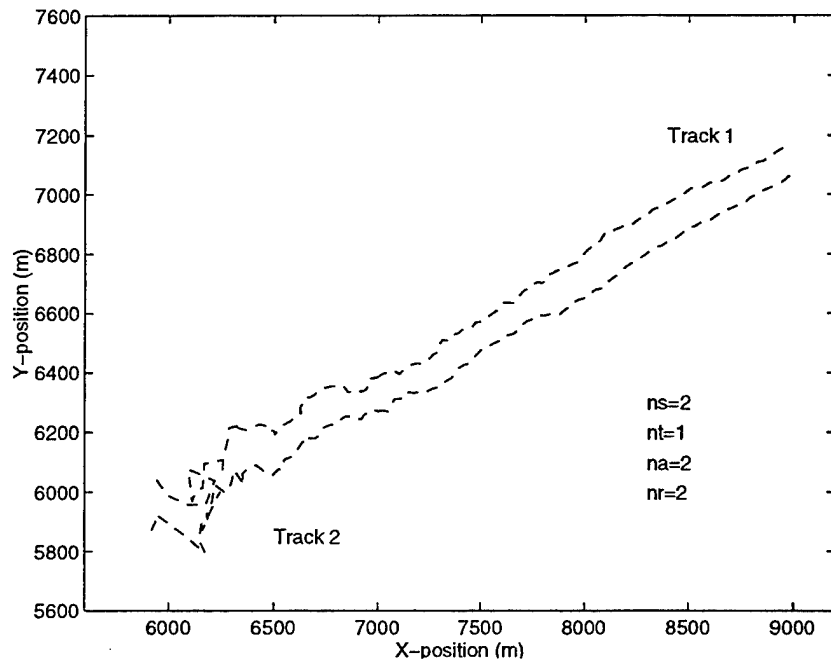


Figure 63. Displayed Tracks Before Fusion (H_1)

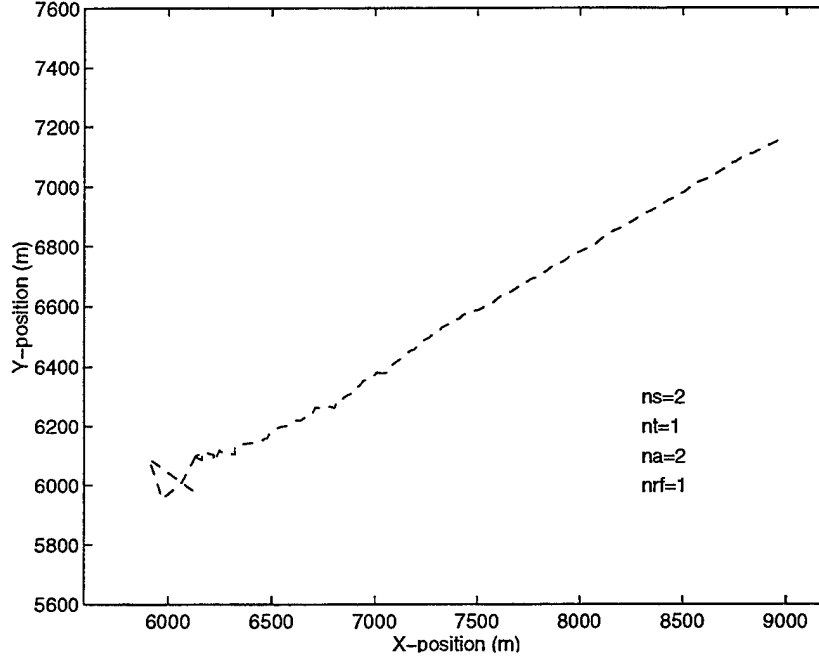


Figure 64. Displayed Tracks After Fusion (H_1)

two tracks \mathbf{R}_i and \mathbf{R}_j from two different sensors i and j respectively, the cross-covariance is defined as

$$E_{ij} = E\{(\mathbf{R}_i - \hat{\mathbf{R}}_i)(\mathbf{R}_j - \hat{\mathbf{R}}_j)\}, \quad (\text{VI.44})$$

where $\hat{\mathbf{R}}_i$ and $\hat{\mathbf{R}}_j$ are the estimates of sensor i and sensor j respectively. Similarly, the cross-resolution of two sensors i and j , with resolutions Δ_i and Δ_j , is defined as

$$\Delta_{ij} = \Delta'_i \Delta_j = \Delta'_j \Delta_i. \quad (\text{VI.45})$$

By inserting the definition of the cross-resolution, given by Equation VI.45, into Equation VI.8, we can write the correlation terms as

$$d_{ij} = \begin{cases} \sqrt{(\mathbf{R}_j - \mathbf{R}_i)'(\mathbf{R}_j - \mathbf{R}_i)}, & \text{if } i \neq j \\ \sqrt{\Delta'_i \Delta_j} = \sqrt{\Delta'_j \Delta_i} = \sqrt{\Delta_{ij}}, & \text{if } i = j. \end{cases} \quad (\text{VI.46})$$

On the basis of these definitions, the optimum degrees of membership are then calculated as:

$$\mu_{11} = \frac{(1/\Delta_{12})^{\frac{1}{m-1}}}{(1/\Delta_{12})^{\frac{1}{m-1}} + (1/(\mathbf{R}_1 - \mathbf{R}_2)'(\mathbf{R}_1 - \mathbf{R}_2))^{\frac{1}{m-1}}}, \quad (\text{VI.47})$$

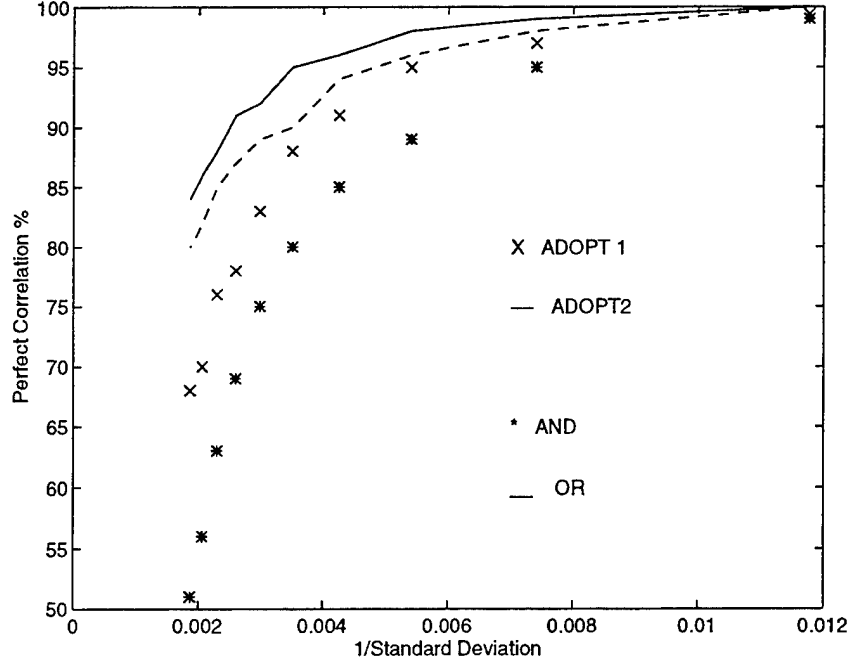


Figure 65. Percentage of Perfect Correlation Under H_1

$$\mu_{12} = \frac{(1/(\mathbf{R}_1 - \mathbf{R}_2)'(\mathbf{R}_1 - \mathbf{R}_2))^{\frac{1}{m-1}}}{(1/\Delta_{21})^{\frac{1}{m-1}} + (1/(\mathbf{R}_2 - \mathbf{R}_1)'(\mathbf{R}_2 - \mathbf{R}_1))^{\frac{1}{m-1}}}, \quad (\text{VI.48})$$

$$\mu_{21} = \frac{(1/(\mathbf{R}_2 - \mathbf{R}_1)'(\mathbf{R}_2 - \mathbf{R}_1))^{\frac{1}{m-1}}}{(1/\Delta_{12})^{\frac{1}{m-1}} + (1/(\mathbf{R}_1 - \mathbf{R}_2)'(\mathbf{R}_1 - \mathbf{R}_2))^{\frac{1}{m-1}}}, \quad (\text{VI.49})$$

$$\mu_{22} = \frac{(1/\Delta_{21})^{\frac{1}{m-1}}}{(1/\Delta_{21})^{\frac{1}{m-1}} + (1/(\mathbf{R}_2 - \mathbf{R}_1)'(\mathbf{R}_2 - \mathbf{R}_1))^{\frac{1}{m-1}}}, \quad (\text{VI.50})$$

and the similarity matrix becomes

$$\mathbf{U} = \begin{pmatrix} \mu_{11} & \mu_{12} \\ \mu_{21} & \mu_{22} \end{pmatrix}, \quad (\text{VI.51})$$

where $\mu_{11} = \mu_{22} = \mu_{CR}$ represents the degree of membership of the cross Resolution, and $\mu_{12} = \mu_{21} = \mu_{CC}$ represents the degree of membership of the cross-correlation between the two tracks. In this case, the similarity matrix is symmetric and there is only one association decision defined as

$$D_g = \begin{cases} 1 \text{ (same tracks),} & \text{if } \mu_{CC} > \mu_{CR} \\ 0 \text{ (different tracks),} & \text{if } \mu_{CC} < \mu_{CR}, \end{cases} \quad (\text{VI.52})$$

where D_g is the global association decision.

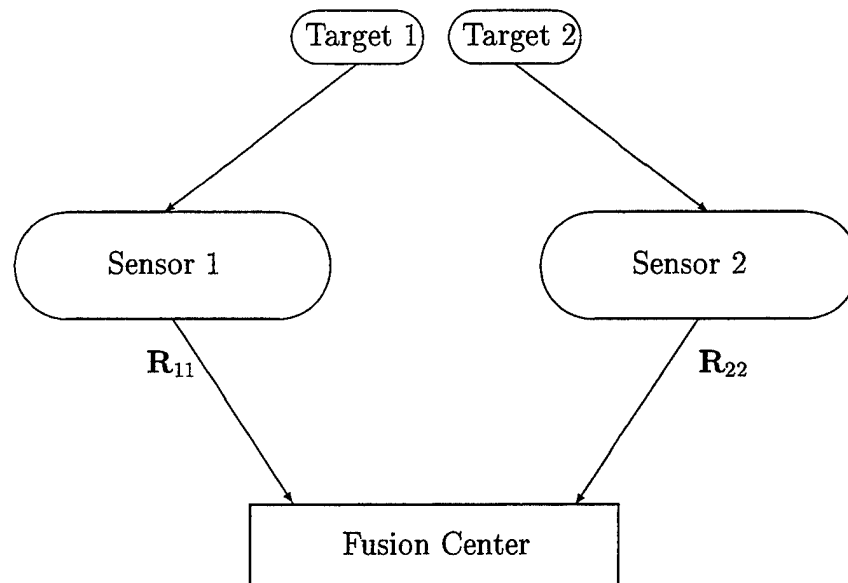


Figure 66. Two Sensors Observing Two Closing Targets (H_0)

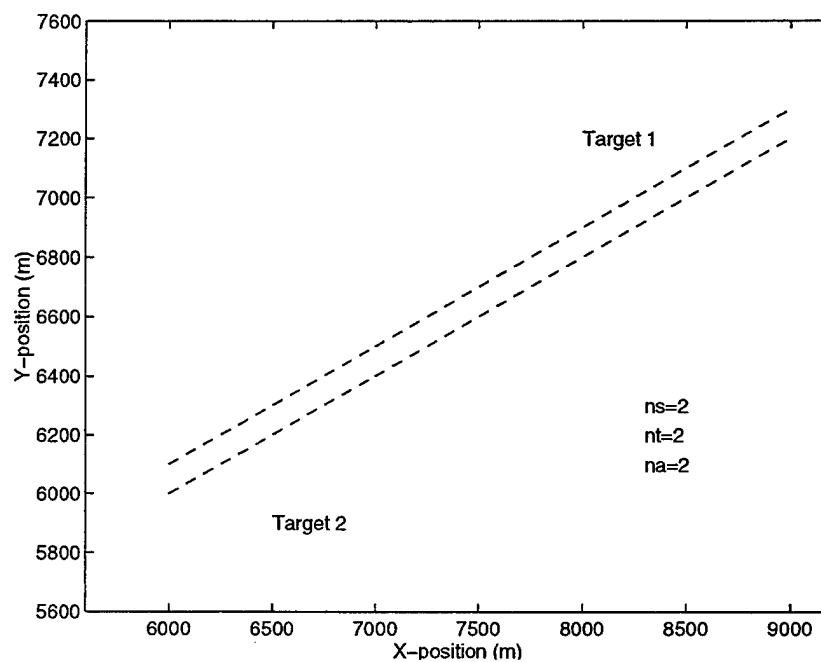


Figure 67. Actual Target Trajectories (H_0)

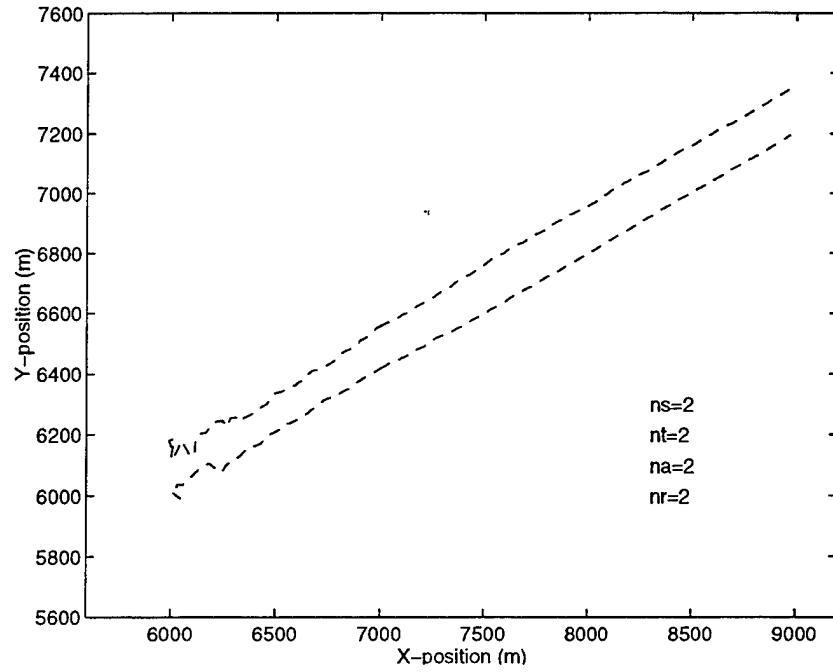


Figure 68. Displayed Tracks Before Fusion (H_0)

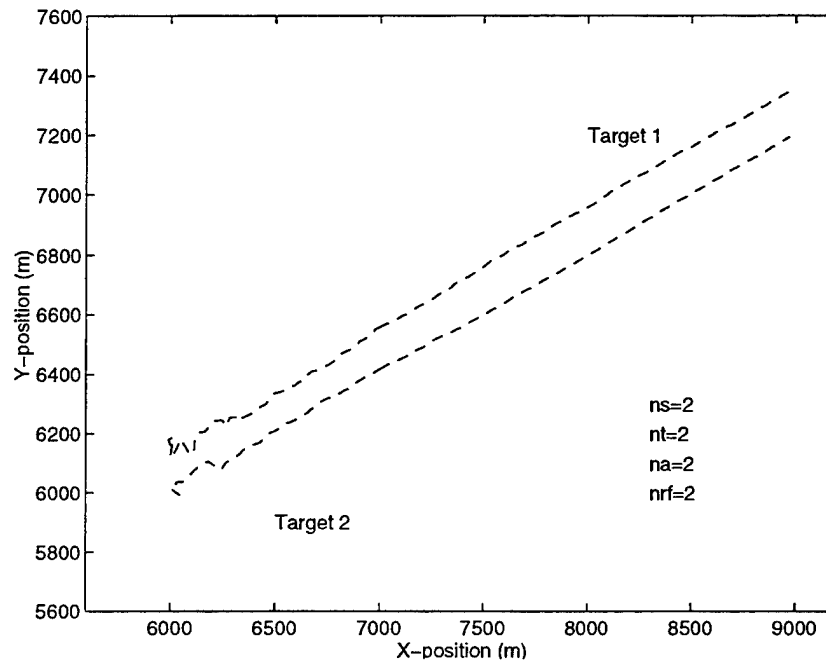


Figure 69. Displayed Tracks After Fusion (H_0)

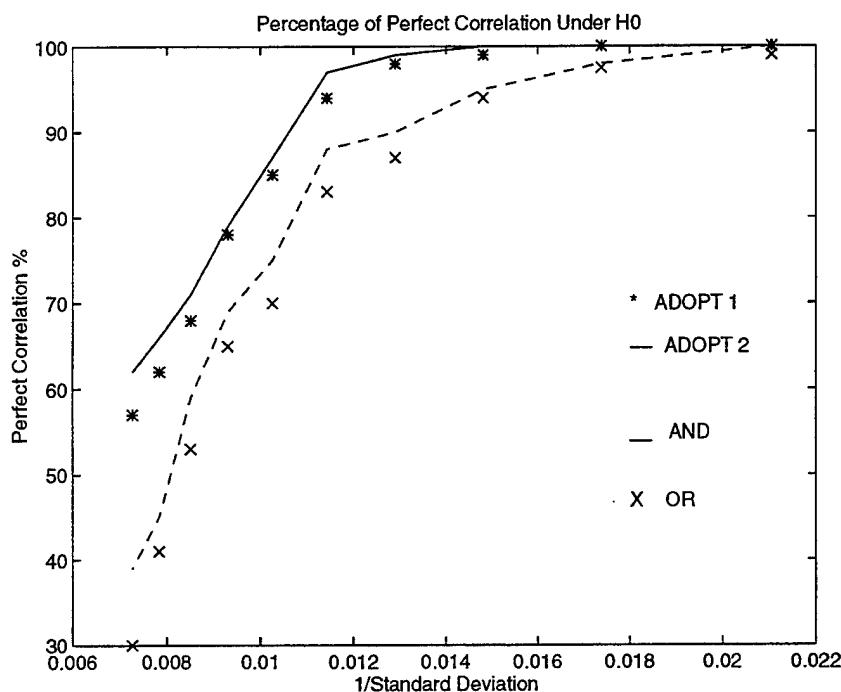


Figure 70. Percentage of Perfect Correlation Under H_0

2. Performance Evaluation and Comparison With Other Association Techniques

We compare the performance of the proposed association rule (based on the cross-resolution) for the two scenarios of the examples of Figures 61 and 66. The performance is determined in terms of the percentage of perfect correlation and is compared to that of the gating techniques, the test statistic, the test statistic using the cross covariance matrix (see Chapter III for the details), *ADOPT 1* fusion rule, *ADOPT 2* fusion rule, Fuzzy *OR* fusion rule, and Fuzzy *AND* fusion rule. The distance measures of Equation VI.8 are determined as

$$d_{ij} = \sqrt{(\mathbf{R}_j - \hat{\mathbf{R}}_i)' \mathbf{C}^{-1} (\mathbf{R}_j - \hat{\mathbf{R}}_i)}, \quad (\text{VI.53})$$

where \mathbf{C} is defined by Equation VI.37.

The results are shown in Figures 71- 74 and Tables XIX and XX. As shown in Figures 71 and 73, the performance of the cross-resolution association rule is better than the performance of *ADOPT 1* and *ADOPT 2* fusion rules and has a comparable performance with respect to the *OR* and the *AND* fusion rules. As shown in Fig-

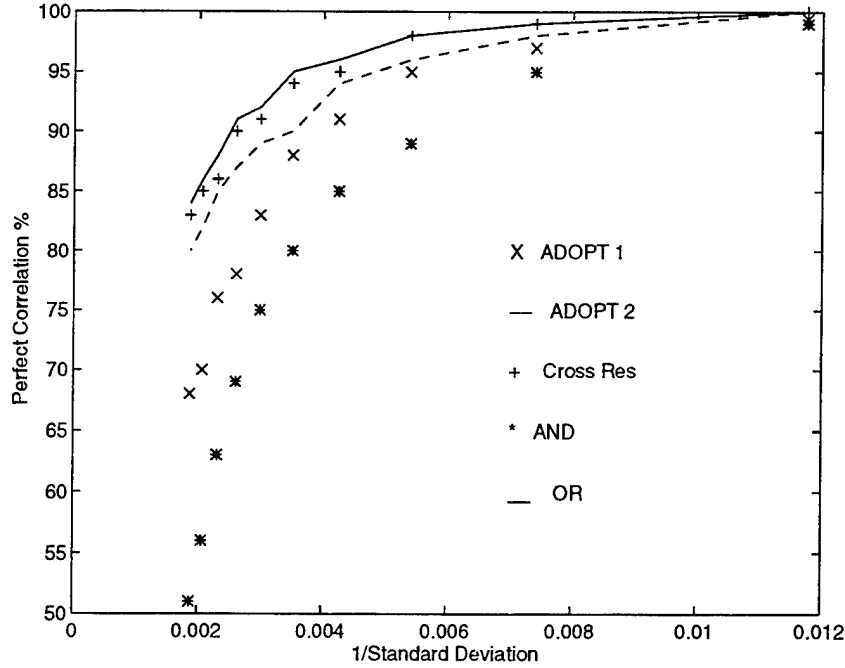


Figure 71. Percentage of Perfect Correlation Under H_1

ures 72 and 74, as the difference between sensor resolutions increases the performance of the cross-resolution association rule degrades and the fusion of association decisions is not recommended. Tables XIX and XX compare the performance of different association techniques for different values of noise uncertainties under hypothesis H_0 and H_1 respectively. The results show that the fuzzy *OR* and *AND* fusion rules perform better than the gating and the test statistic techniques. The performance of the cross-resolution degrades considerably when the sensors have very different uncertainties.

E. TRACK-TO-TRACK ASSOCIATION AND TRACK FUSION OF DIFFERENT DIMENSIONALITY ESTIMATES

In the previous section, we considered track-to-track association and track fusion when different tracks have the same number of attributes. Also, we assumed that the most accurate sensor has better performance for all individual attributes. When this is not the case, the proposed fuzzy clustering approach can easily be

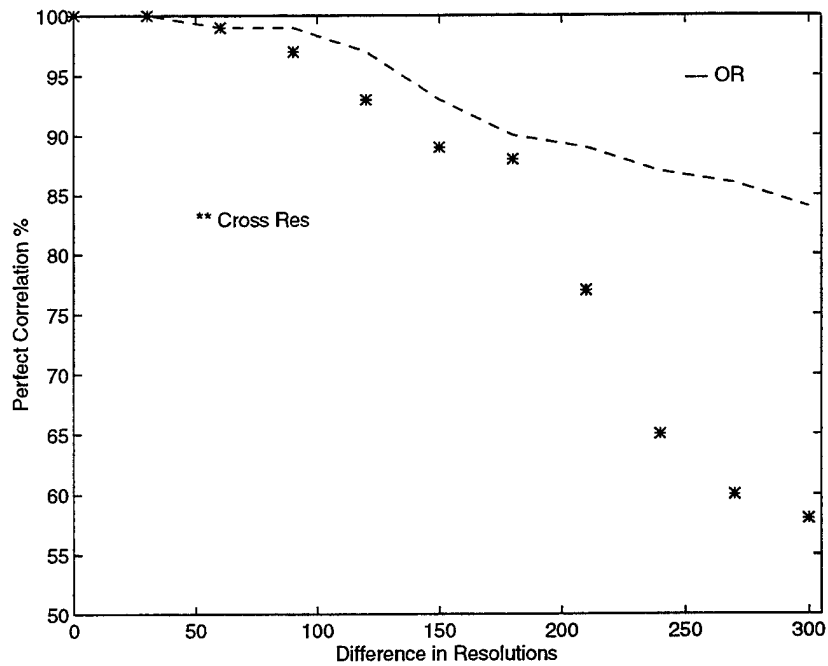


Figure 72. Percentage of Perfect Correlation Under H_1

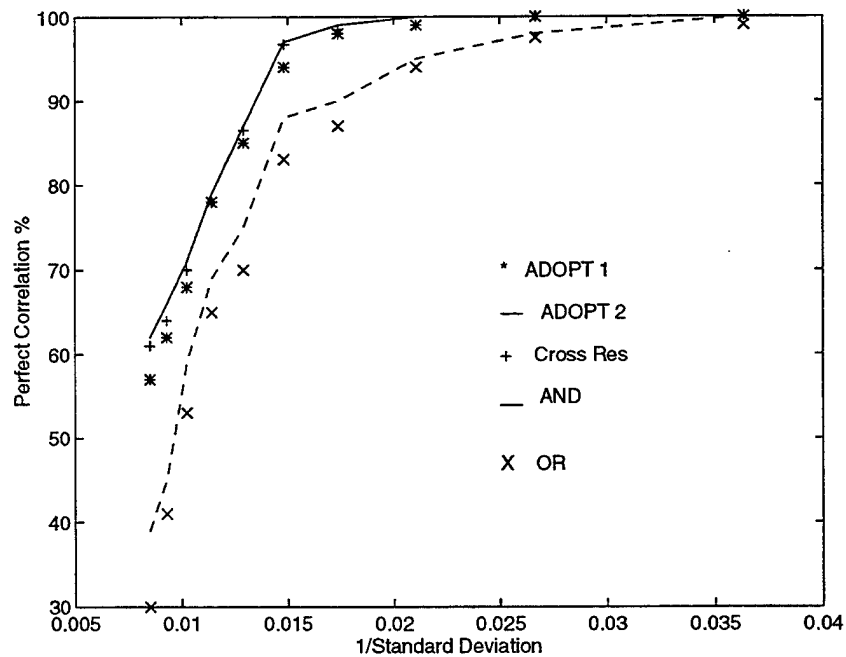


Figure 73. Percentage of Perfect Correlation Under H_0

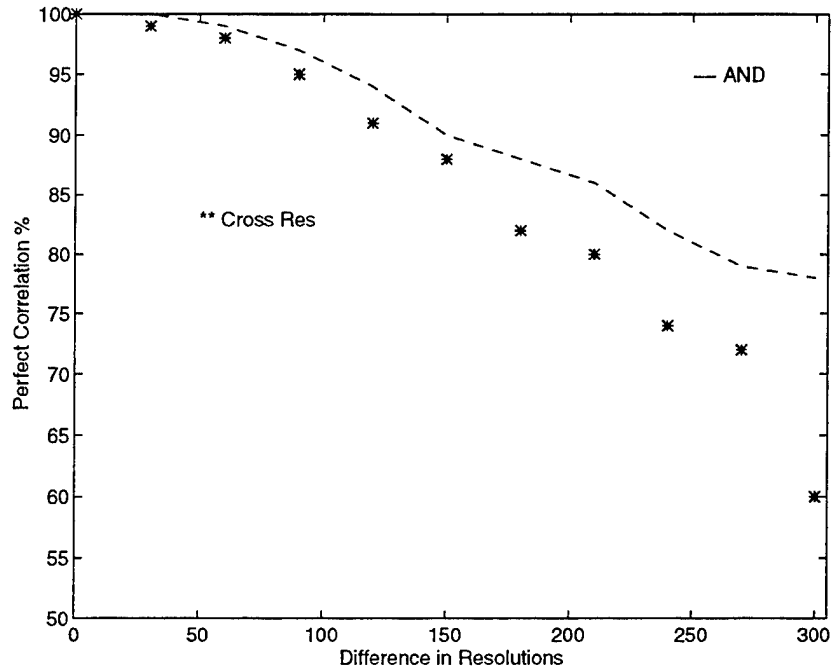


Figure 74. Percentage of Perfect Correlation Under H_0

Table XIX. Comparison of Classical and Fuzzy Techniques Under Hypothesis H_1

Sensors Uncertainties	Gating Tech.	Test Stat.	Cross Cov.	Cross Res.	Fuzzy OR
$\sigma_{x1} = 30, \sigma_{y1} = 40, \sigma_{x2} = 70, \sigma_{y2} = 90$	96.5 %	98 %	99.1 %	98.5 %	99 %
$\sigma_{x1} = 30, \sigma_{y1} = 40, \sigma_{x2} = 90, \sigma_{y2} = 130$	92 %	97 %	98.5 %	97.5 %	98.5 %
$\sigma_{x1} = 30, \sigma_{y1} = 40, \sigma_{x2} = 190, \sigma_{y2} = 220$	86 %	92 %	97.5 %	96.5 %	97.5 %
$\sigma_{x1} = 30, \sigma_{y1} = 40, \sigma_{x2} = 300, \sigma_{y2} = 400$	73 %	90 %	93 %	89 %	93 %

Table XX. Comparison of Classical and Fuzzy Techniques Under Hypothesis H_0

Sensors Uncertainties	Gating Tech.	Test Stat.	Cross Cov.	Cross Res.	Fuzzy <i>AND</i>
$\sigma_{x1} = 30, \sigma_{y1} = 40, \sigma_{x2} = 70, \sigma_{y2} = 90$	60 %	99.5 %	99.6 %	96.5 %	99.5 %
$\sigma_{x1} = 30, \sigma_{y1} = 40, \sigma_{x2} = 90, \sigma_{y2} = 130$	55 %	96 %	99.2 %	95 %	99 %
$\sigma_{x1} = 30, \sigma_{y1} = 40, \sigma_{x2} = 190, \sigma_{y2} = 220$	48 %	91 %	98 %	89 %	98 %
$\sigma_{x1} = 30, \sigma_{y1} = 40, \sigma_{x2} = 300, \sigma_{y2} = 400$	35 %	87 %	93 %	63 %	93 %

utilized as explained below.

Consider a number of reports n_r from different sensors n_s , with number of attributes $n_{a_n}, n = 1, 2, \dots, n_s$, not necessarily the same, i.e.,

$$n_{a_i} \neq n_{a_j} \text{ for sensors } i \text{ and } j, \quad (\text{VI.54})$$

where n_{a_i} and n_{a_j} are the number of attributes of sensors i and j respectively. Sensor i may have a better estimate for an attribute a_1 , while it may have a worse estimate for attribute a_2 , i.e.,

$$\begin{aligned} \Delta_i(a_1) &< \Delta_j(a_1), \\ \Delta_i(a_2) &> \Delta_j(a_2). \end{aligned} \quad (\text{VI.55})$$

The problem is to develop a fuzzy track-to-track association and track fusion algorithm for the previous case in an unsupervised mode of operation. We also want to determine the dominant track, when two or more tracks represent the same target. The dominant track is defined as the track that has the most accurate estimates among

all the individual sensor attribute estimates. We define two modes of operation: sequential and parallel clustering.

1. Sequential Clustering

In case of sequential clustering, the tracks are clustered and fused sequentially as shown in Figure 75. Given two tracks i and j having the same attribute a , we determine the distance measure as

$$d_{ij}(a) = \begin{cases} |\mathbf{R}_j(a) - \mathbf{R}_i(a)| & \text{if } i \neq j \\ \Delta_i(a) & \text{if } i = j. \end{cases} \quad (\text{VI.56})$$

The similarity matrix is obtained using Equation VI.13 as

$$\mu_{ij}(a) = \frac{(1/d_{ij}(a))^{\frac{2}{m-1}}}{[\sum_{s=1}^2 (\frac{1}{d_{sj}(a)})^{\frac{2}{m-1}}]}, \quad (\text{VI.57})$$

which can be written in a matrix form

$$\mathbf{U}(a) = \begin{pmatrix} \mu_{ii}(a) & \mu_{ij}(a) \\ \mu_{ji}(a) & \mu_{jj}(a) \end{pmatrix}. \quad (\text{VI.58})$$

The association decision rule is the same decision rule of Equation VI.19. When it is decided the two tracks are the same, the dominant track is determined as follows

$$\mathbf{R}_{dom}(a) = \mathbf{R}_i(a) \text{ if } \mu_{ii}(a) > \mu_{jj}(a), \quad (\text{VI.59})$$

$$\mathbf{R}_{dom}(a) = \mathbf{R}_j(a) \text{ if } \mu_{ii}(a) < \mu_{jj}(a),$$

i.e.,

$$\mathbf{R}_{dom}(a) = \mathbf{R}_n(a), \quad (\text{VI.60})$$

where

$$n = \operatorname{argmax}(\mu_{ii}(a)). \quad (\text{VI.61})$$

2. Parallel Clustering

In case of parallel clustering, all tracks are clustered and fused at the same time as shown in Figure 76. In this case, the association decision and the dominant track

are obtained using Equations VI.19 and VI.60, respectively, taking into consideration all the similarity measures of VI.13 at the same time for a given attribute.

The sequential and parallel clustering are equivalent in terms of the performance of the correct data association and the performance of the dominant track. However, the parallel clustering is faster than the sequential clustering since it requires the computation of s^2 elements for each attribute a , as opposed to $2s(s - 1)$ elements in case of sequential clustering, where s is the number of tracks that represent the same target. The number of comparisons, for a given attribute, is the same for both clustering and is equal to $s - 1$.

The performance of the dominant track is compared to that of the individual sensor performance for the example of Figure 61. We assume that sensor 1 has a better accuracy in x -position while sensor 2 has a better accuracy in y -position. The sensor uncertainties are assumed to be

$$\sigma_{x_1} = 90 \text{ m}, \quad (\text{VI.62})$$

$$\sigma_{y_1} = 150 \text{ m},$$

$$\sigma_{x_2} = 170 \text{ m},$$

$$\sigma_{y_2} = 80 \text{ m}.$$

The sensor resolutions are assumed to be

$$\Delta_i = 3 \begin{pmatrix} \sigma_{x_i} \\ \sigma_{y_i} \end{pmatrix}, i = 1, 2. \quad (\text{VI.63})$$

We assume that the x and y positions are taken every 0.1 second. We processed 200 measurements (20 seconds of data) over 1000 Monte Carlo simulations, and the performance of the dominant track has been evaluated in terms of the mean square error, defined as

$$e = \sqrt{e_x^2 + e_y^2} = \sqrt{(x_{true} - \hat{x})^2 + (y_{true} - \hat{y})^2}. \quad (\text{VI.64})$$

The mean square error of the dominant track is also compared to that of the individual sensor mean square errors. The results, shown in Figure 77, indicate that the

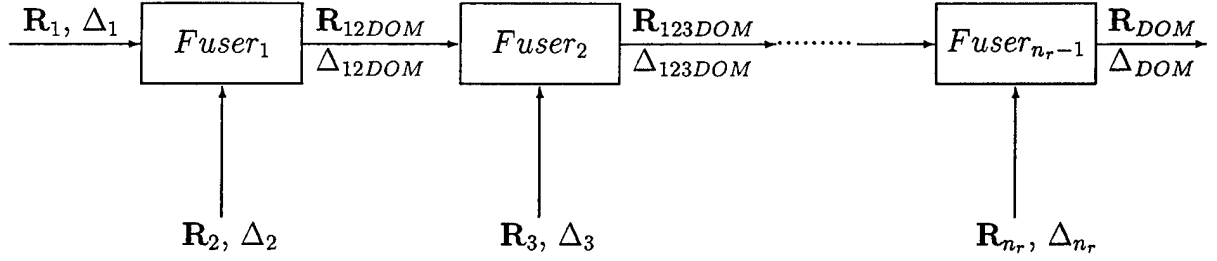


Figure 75. Sequential Clustering

dominant track yields a better estimate than the individual sensor itself. The results also show the efficiency of the proposed clustering approach in terms of correct association and performance of the dominant track.

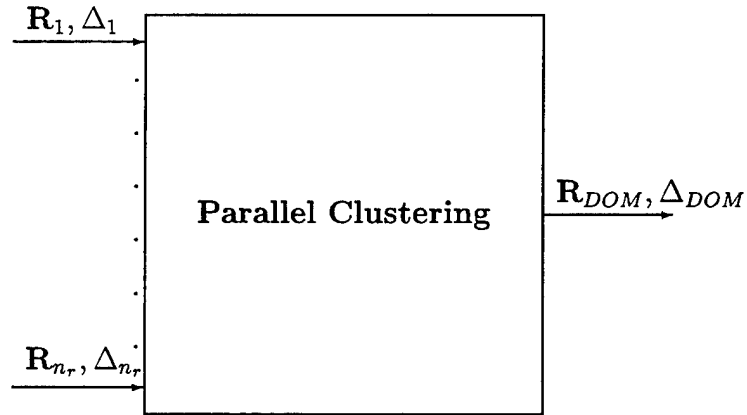


Figure 76. Parallel Clustering

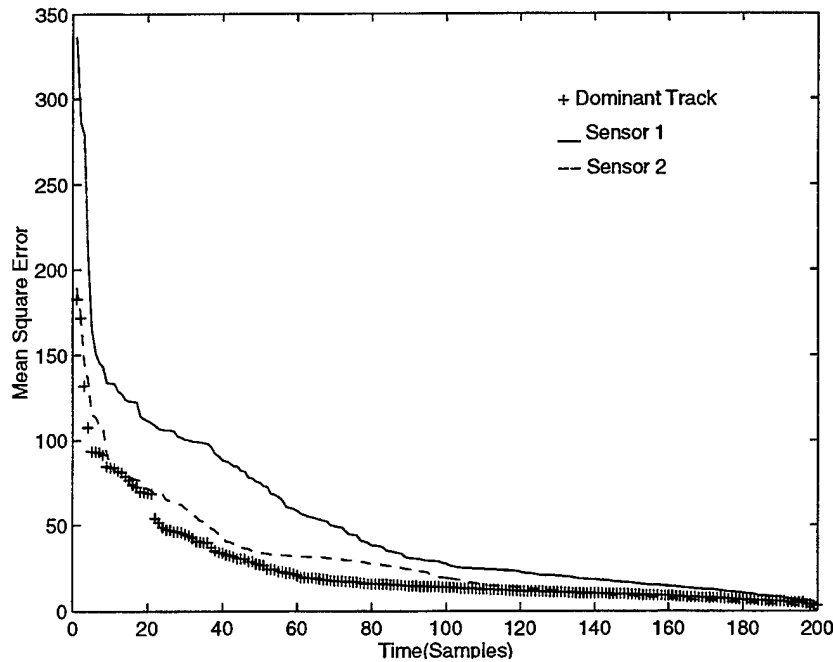


Figure 77. Performance of the Dominant Track as Well as the Individual Sensor Performances

F. APPLICATION OF FUZZY CLUSTERING TO TRACK ASSOCIATION IN OVER-THE-HORIZON RADAR

Over The Horizon Radar (*OTHR*) provides surveillance of the air space and ocean, and it has been adopted by many countries such as Australia [Ref. 121, 132], where it has been used successfully for remote sensing of air space and sea conditions and detecting and tracking remote targets. The *OTHR* uses the ionosphere layers in the sky as a reflection medium for the high frequency signals. The problem is that multiple ionosphere layers cause several tracks per target to be observed at the receiver. For example, with two ionosphere layers each target produces up to four tracks, as illustrated in Figures 78 and 79 which show the four possible reflection paths. This problem, which is called the multiple tracks common source (*MTCS*) problem, causes a degradation in the performance of target tracking and identification. An association approach is essentially needed to merge the *MTCS* tracks into unique set of tracks that represent the true number of targets.

There are many approaches in the literatures to associate *MTCS* [Ref. 12, 121,

122, 132]. The classical technique requires hypothesizing the states of the ionosphere conditions, including the number of ionosphere layers and the height for each layer and testing each hypothesized track against observed tracks [Ref. 178]. This solution is computationally expensive. Furthermore, it assumes stationarity of the ionosphere layers which might not be realistic, since the ionosphere layers tend to change rapidly due to many phenomena related to wind, season, and sun. The neural networks are also used to solve this problem [Ref. 12, 132]. Neural networks requires training of such approaches with a very large set of tracks representing the *OTHR* tracking system.

The proposed fuzzy clustering approach (Section A) can be used to associate the *MTCS* tracks which belong to the same target. To demonstrate the feasibility of the proposed approach to solve *MTCS* problem, it is applied to an example of two *OTHRs* detecting one target in a two ionosphere layer environment. The same target is tracked simultaneously by the two *OTHRs*. The detected tracks are reported to a data fusion center and they are shown in Figure 80. The data fusion center receives eight tracks representing four reflections for each *OTHR*. Each track consists of bearing (θ) and range (r) information of the observed target, i.e.

$$\mathbf{R}_i = \begin{pmatrix} \theta_i \\ r_i \end{pmatrix}, i = 1, 2, \dots, 8. \quad (\text{VI.65})$$

The sensor uncertainties are represented by the covariance matrix

$$\mathbf{C}_j = \begin{pmatrix} \sigma_{\theta j}^2 & 0 \\ 0 & \sigma_{rj}^2 \end{pmatrix}, j = 1, 2,$$

where $\sigma_{\theta j}^2$ and σ_{rj}^2 represent the variances of the measurements errors of bearing and range information respectively. The reflections from the ionosphere layers cause additional errors in bearing and range measurements. These errors are assumed to be normally distributed with zero mean and variances $\sigma_{\theta \ell}^2$ and $\sigma_{r \ell}^2$ in bearing and range respectively. The sensors and layers variances are assumed to be $\sigma_{\theta} = 0.5$ Radians, $\sigma_r = 50$ km, $\sigma_{\theta \ell} = 0.6$ Radians, and $\sigma_{r \ell} = 90$ km. The eight tracks received before

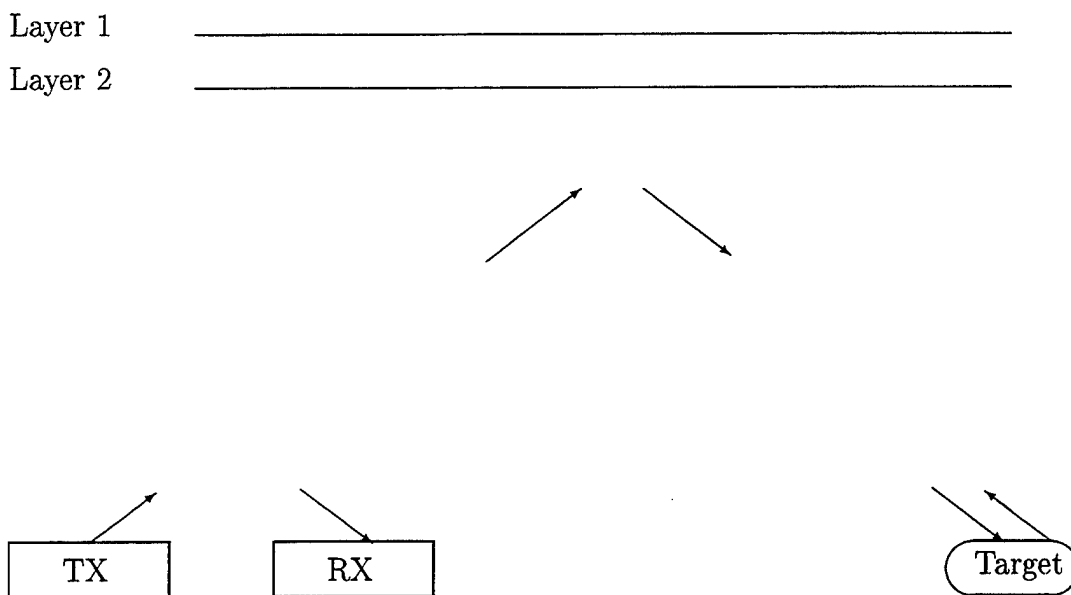


Figure 78. An Over-the-Horizon Radar System Detecting One Target in Two Ionosphere Layers Environment

fusion are shown in Figures 80, while the fused tracks are shown in Figure 81. In the case of one simulated target, the proposed approach seems to yield satisfactory results. Testing with real data and multiple targets need to be performed to validate the effectiveness of the proposed algorithm.

G. APPLICATIONS TO REAL DATA OBTAINED FROM THE UNITED STATES COAST GUARD VESSEL TRAFFIC SERVICES SYSTEM

A real example of a *MSMT* environment, in overlapping coverage scenario, is the United States Coast Guard (*USCG*) Vessel Traffic Services (*VTS*) system, where the targets are vessels in the harbors and waterways in the continental *USA* and the sensors include radar tracks, Global Position System *GPS* tracks, and Standard Routes *SR* tracks, as shown in Figure 82. The *GPS* tracks are sent automatically through radio links from the vessels. The *SR* tracks are computer generated tracks, which are used by the operator when the observed vessel has a non reporting status due to a failure. The *SR* tracks are based on the last reported information of the vessel

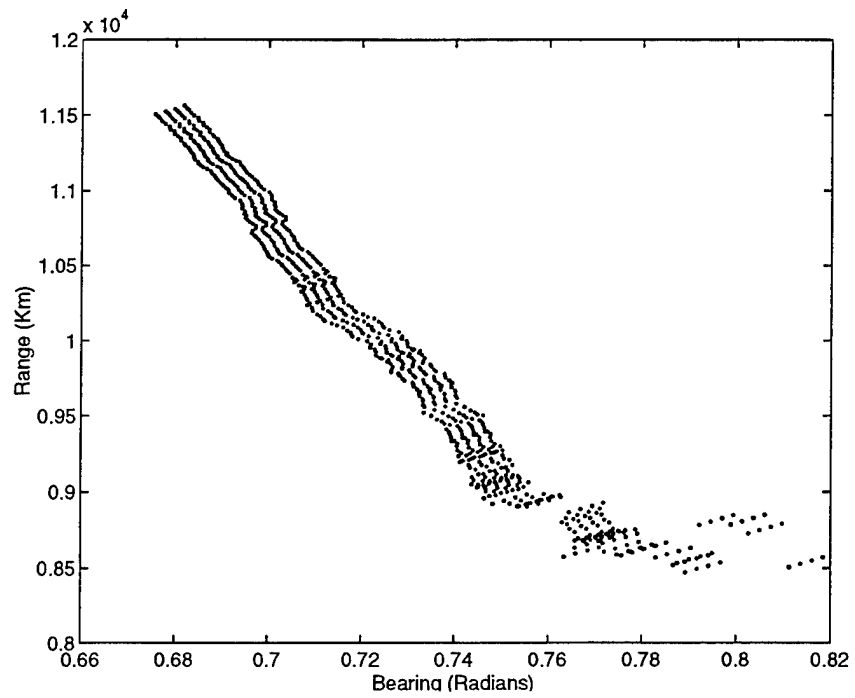


Figure 79. An Example of Multiple Tracks Common Source (four tracks are displayed)

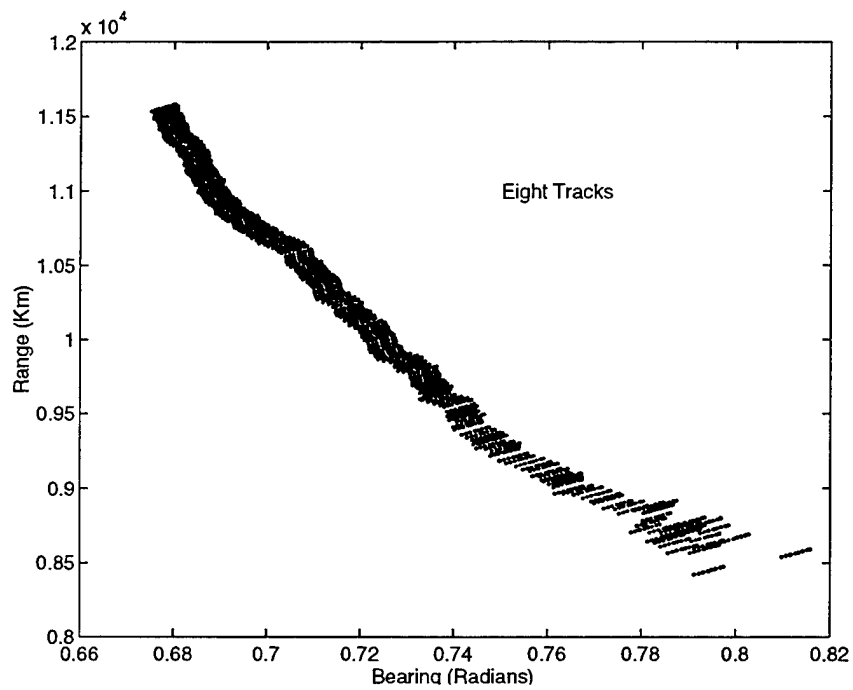


Figure 80. Displayed Tracks Before Fusion

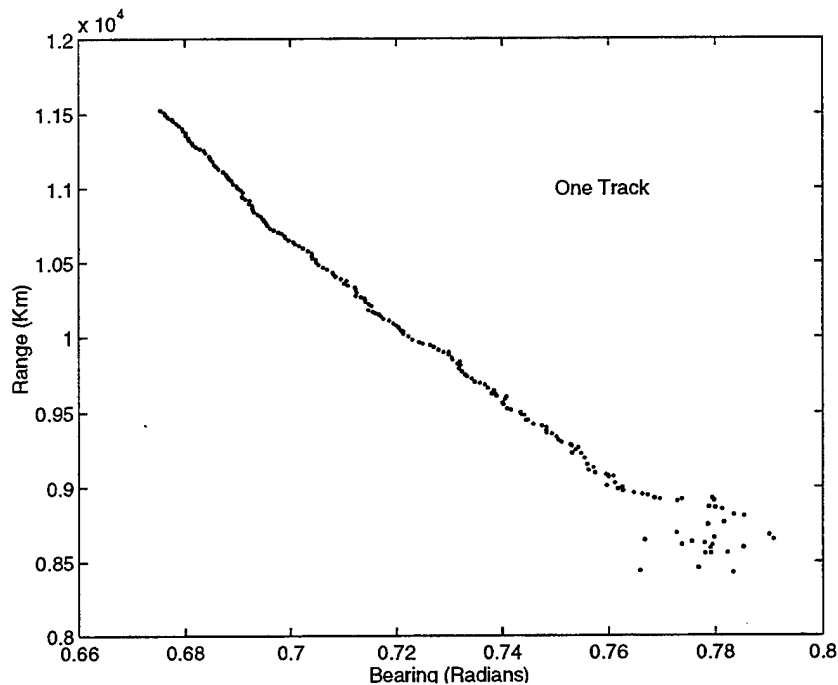


Figure 81. Displayed Tracks After Fusion

(position, bearing, ...etc). A detailed description of the *VTIS* system and different types of sensors can be found in [Ref. 75, 76, 77, 131].

All sensor types report information (attributes) about the observed vessels, to a data fusion center called track data base manager (*Tdbm*). The *Tdbm* is responsible for processing all the reported information to eliminate the redundant tracks. For each scan, the reported information are vessel name, time of report, tracking status (sensor type, e.g. radar, *GPS*, *SR*), track I.D. (track number), sensor track number (e.g. radar track number or sensor track number), course (in degrees), speed (in knots), latitude (in degrees and minutes), longitude (in degrees and minutes), vessel size (length of vessel), and track quality. A more in depth description of the different information reported to the *Tdbm* can be found in [Ref. 75, 77].

The proposed track-to-track association and track fusion approach is applied to real data collected from *U.S.* Coast Guard *VTIS* Puget Sound and *VTIS* San Francisco (see [Ref. 181] for more details). The results show that the proposed approach successfully fused the reported tracks and selected the superior tracks in all considered

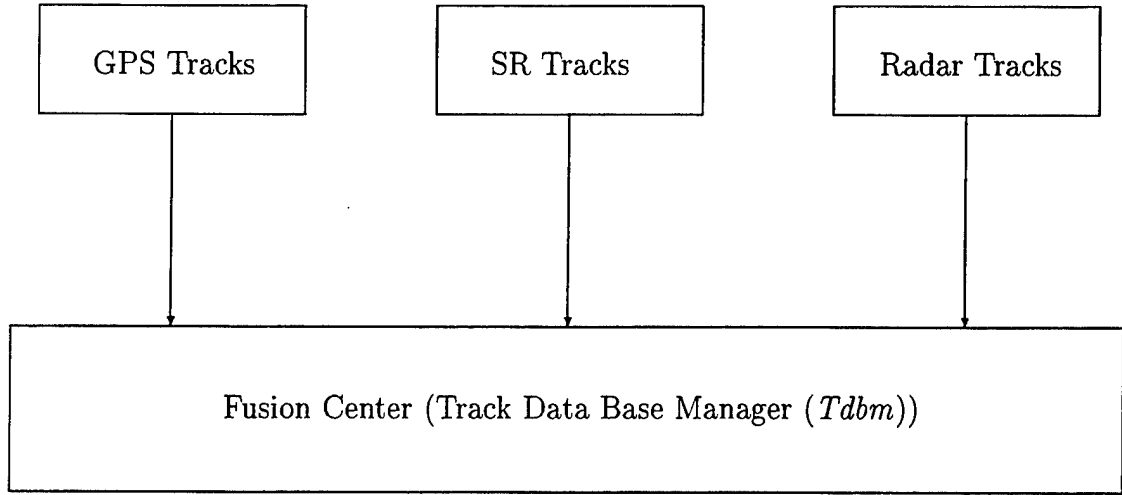


Figure 82. Overview of the *VTS* System

scenarios. Here, we present the results in the following scenarios:

Scenario 1: Two radars observe a single vessel in an overlapping coverage scenario. The tracks are identified by *ID* numbers 830 and 831. The superior track is track 831.

Scenario 2: Two radars observe a single vessel in an overlapping coverage scenario (*ID* numbers 806 and 807). The superior track is track 807.

Scenario 3: Two radars observe a single vessel (*ID* numbers 750 and 751, track 751 is the superior track) along with a third radar that observes a different vessel (track 757). Initially, track 751 is the superior track. When track 751 is terminated, track 750 is adopted.

Scenario 4: Two radars (*ID* numbers 772 and 774) and *GPS* track (*ID* number 773) observe a single vessel. The priority of the superior tracks is track 773, track 772, then track 774. Initially, the superclustering algorithm adopts track 773 as the superior track. When track 773 is terminated, the superiority is handed to track 772. Finally, track 774 is adopted.

The track-to-track association of scenarios 1 and 2 processes longitude and latitude information while latitude, longitude, and course information are processed for scenarios 3 and 4. The results are plotted in Figures 83- 90 in terms of the displayed tracks before and after fusion. In all scenarios, the fuzzy clustering algorithm successfully fused the redundant tracks and displayed the superior tracks. The results show the efficiency of the proposed fuzzy clustering approach to associate and fuse tracks obtained from different sensors in real and practical examples.

In summary, track-to-track association and track fusion in multisensor-multitarget multiple-attribute environment with overlapping sensor coverage have been considered in this chapter. A fuzzy clustering technique employing track-to-track association and a fuzzy superclustering technique employing track fusion have been proposed. The performances of the proposed algorithms have been evaluated using computer simulations and marine traffic data obtained from the United States Coast Guard Vessel Traffic Services System.

Overall, the proposed techniques performed satisfactory under all simulated and real scenarios. We observed that the performance of the fused track may be worse than the performance of the superior track alone. In general, track fusion would yield the best estimate when the sensors have the same resolutions; however, when the sensor resolutions vary widely, it is better to adopt the superior track rather than fusing the tracks.

The proposed fuzzy track-to-track association and track fusion approach has several advantages. The membership functions are generated from the data using the fuzzy clustering means algorithm, and they are not fixed *a priori*. As a consequence, the values of the degrees of membership change according to the positions of the targets relative to the sensors. Also, the proposed approach can treat all the reported tracks at once, thus avoiding conflicting track-to-track associations. The proposed approach assigns only one degree of membership to each attribute vector rather than one degree of membership to each individual attribute. This reduces the sensitivity of the association decision to individual attribute fluctuations, reduces the number

of rules by a factor of n_a , where n_a is the total number of attributes, and has the advantage of the soft decision over the hard-decision (see Figure 91). The superior track is determined automatically in an unsupervised mode based on the values of the sensor resolutions as well as the observed measurements.

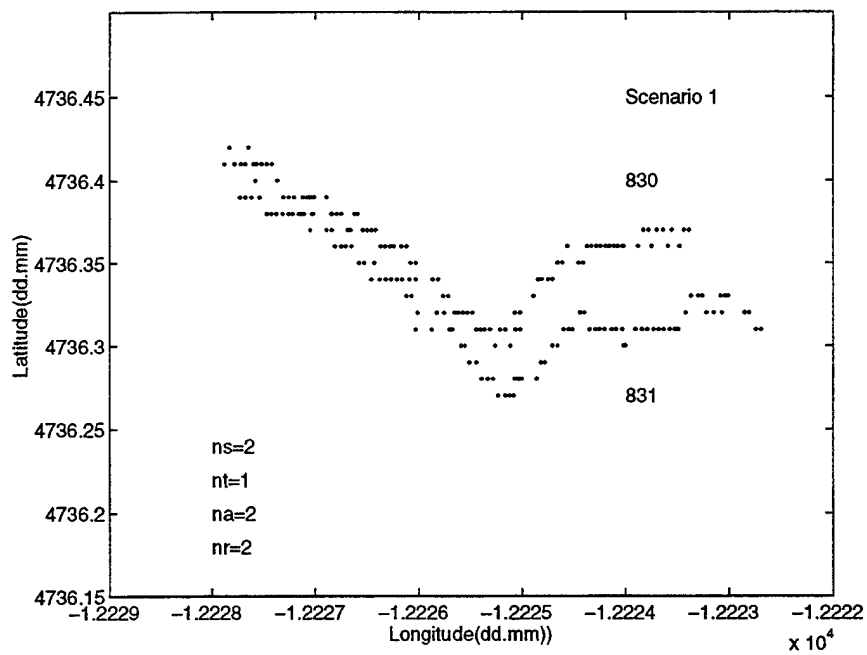


Figure 83. Displayed Tracks Before Fusion for Scenario 1

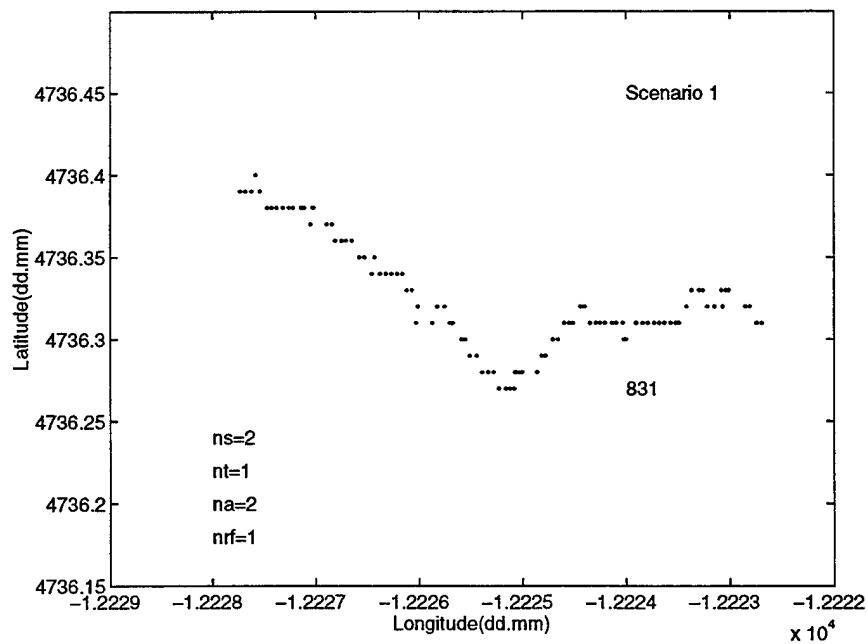


Figure 84. Displayed Tracks After Fusion for Scenario 1

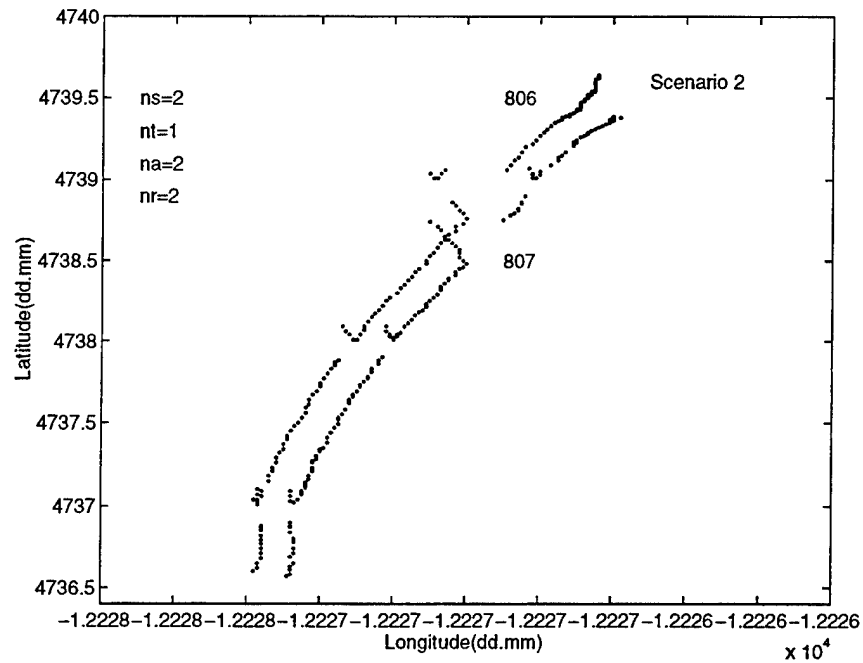


Figure 85. Displayed Tracks Before Fusion for Scenario 2

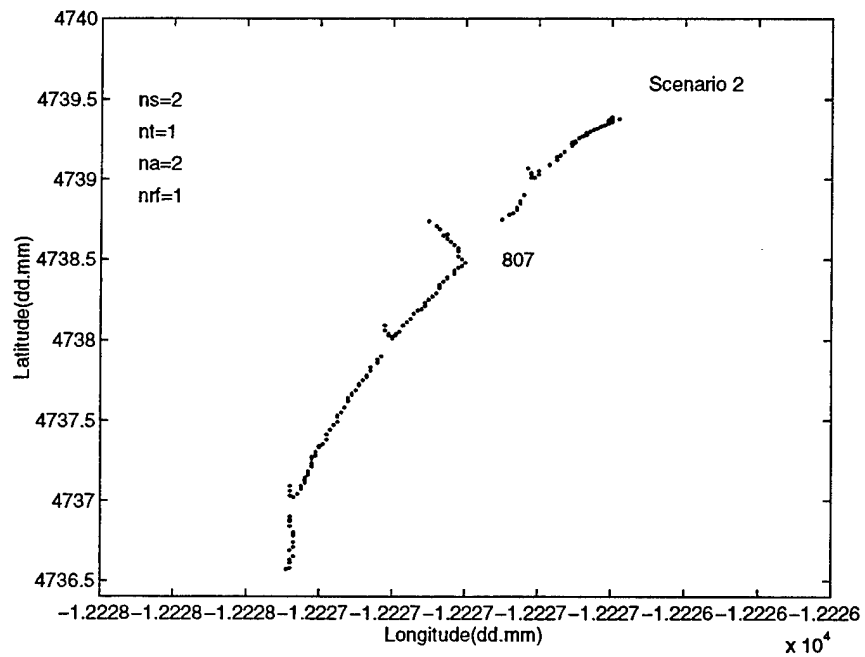


Figure 86. Displayed Tracks After Fusion for Scenario 2

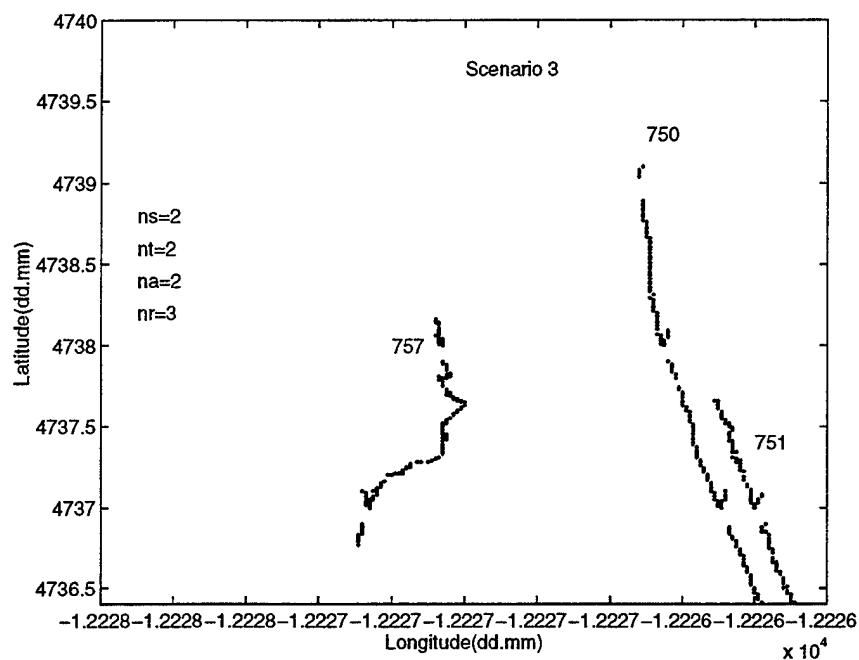


Figure 87. Displayed Tracks Before Fusion for Scenario 3

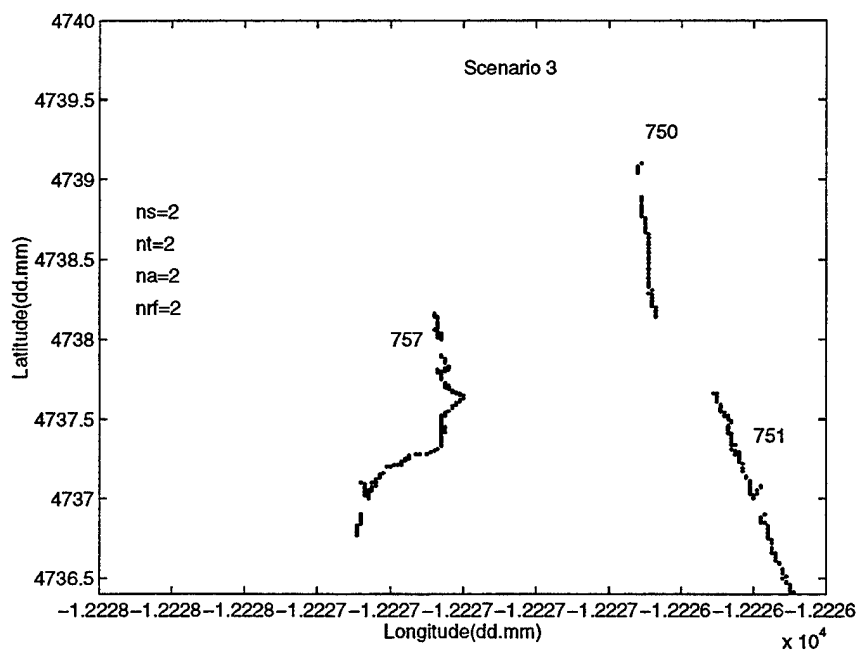


Figure 88. Displayed Tracks After Fusion for Scenario 3

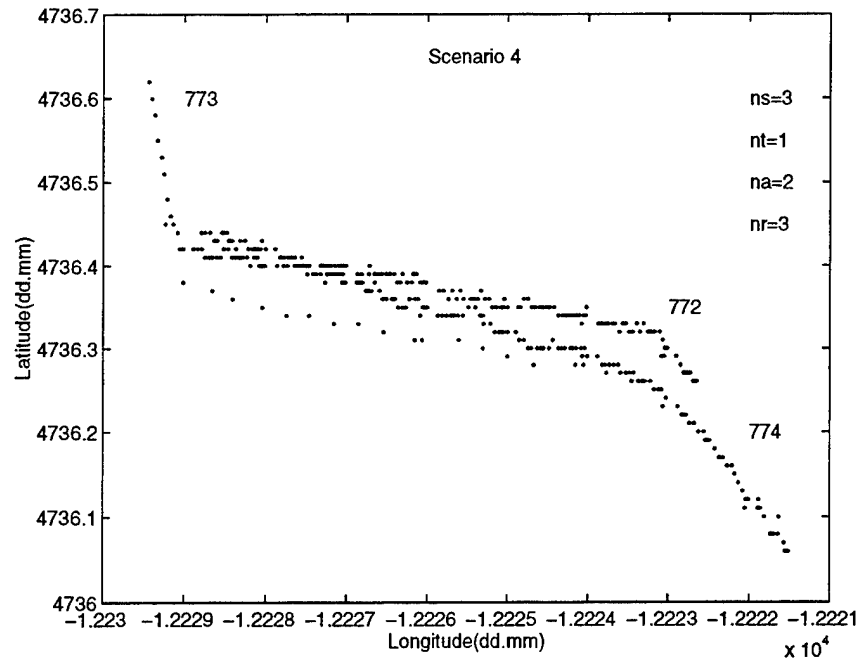


Figure 89. Displayed Tracks Before Fusion for Scenario 4

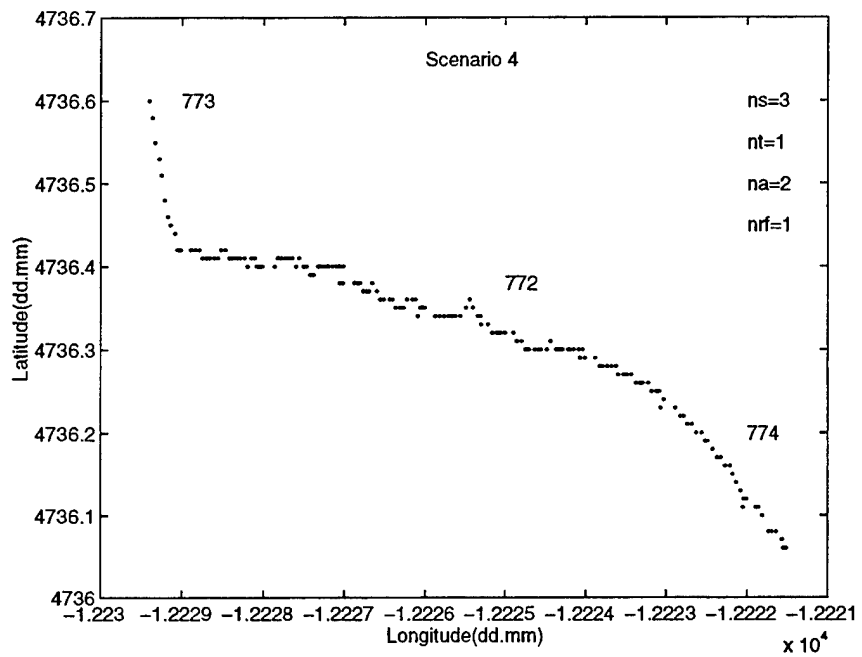


Figure 90. Displayed Tracks After Fusion for Scenario 4

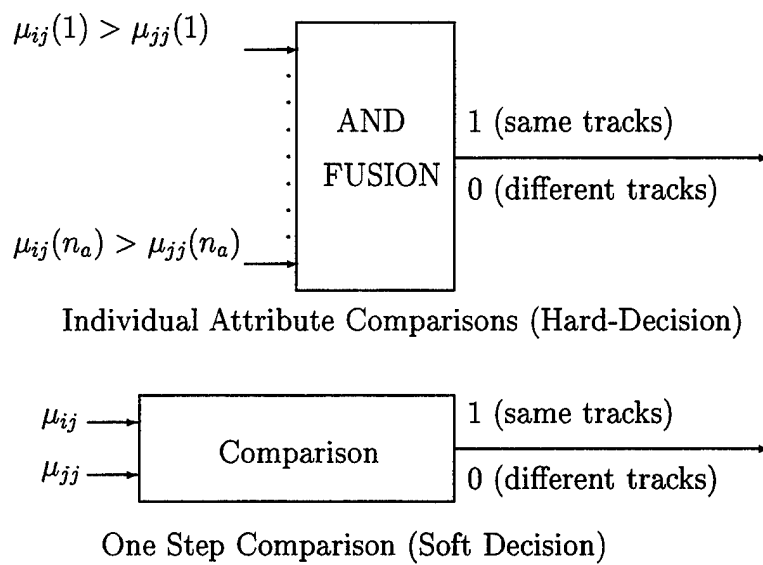


Figure 91. Comparison of Hard and Soft Decisions

VII. IMPROVEMENT OF DATA ASSOCIATION VIA DETECTION USING MULTIPLE-SENSOR

The primary function of sensor fusion is the detection of targets. Given the existence of targets, the next function is the estimation of parameters of the detected targets followed by their association to the existing targets. Intuitively, the higher the detection probability the higher is the correct data association. If a target is falsely detected, the performance of data association is ruined [Ref. 22]. The problem of decision fusion in distributed sensor systems is considered in this chapter [Ref. 1, 50, 52, 193, 195, 183]. Distributed sensors send their decisions to a fusion center that combines all the received decisions from the various sensors into a final global decision [Ref. 51, 53]. Two major approaches for combining the sensor information are analyzed here, and optimum fusion rules for distributed sensor decisions are discussed. Also, a fuzzy decision approach for data fusion in multisensor distributed detection systems is proposed. Simulation examples with Gaussian and exponential distributed observations are considered.

A. DECISION FUSION IN MULTIPLE SENSORS DISTRIBUTED DETECTION SYSTEMS

The problem of multiple sensors surveillance has attracted the attention of several investigators [Ref. 50]. This interest has been sparked by the requirement of military surveillance systems to be more reliable and immune to electronic attack by using multiple sensors rather than single sensor systems. The goal of such multiple sensor systems is to improve system detection performance. This can be achieved by integrating the information obtained from the various sensors. There are two major approaches for combining the information obtained from multiple-sensor distributed detection systems. The first approach is the centralized detection system, where all sensor observations are transmitted to a central processor to derive a global decision.

This requires transmission of sensor observations without delay, which requires a large communication bandwidth. The second approach is the decentralized detection with fusion, where signal processing is distributed among the sensors and a fusion center. The sensors are allowed to derive local decisions; then the fusion center is responsible for combining these local decisions from the various sensors into a global decision. The decentralized approach is appropriate when there are constraints on the amount of information that can be sent to the data fusion center. However, in the absence of this limitation, the best strategy is to transmit individual sensor observations to a central decision processor. Because of such considerations as communication bandwidth and the problem of flooding the fusion processor with more information than it can handle, the centralized detection systems are not usually implemented in practice. Despite the possible performance loss due to local processing, the decentralized approach has the important practical advantage of requiring low bandwidth data links between the sensors and the fusion processor.

1. Centralized Detection Systems

In this approach, all sensor observations are transmitted to a central processor in order to derive a global decision u_0 [Ref. 50]. This approach is depicted in Figure 92 for two sensors and one target. No local decisions are made by the sensors. Under each hypothesis, the sensor observations have known joint probability densities $f(\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n | H_0)$ and $f(\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n | H_1)$, where \mathbf{y}_i , $i=1,2,\dots,n$, are random vectors representing the sensor observations. The crux of the centralized hypothesis testing problem is to derive a decision strategy of the form:

$$u_0 = \begin{cases} 0, & H_0 \text{ is declared to have been detected} \\ 1, & H_1 \text{ is declared to have been detected,} \end{cases} \quad (\text{VII.1})$$

where u_0 depends on the observations $\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n$. According to Neyman-Pearson criterion, it is required to find a decision strategy expressed as a density function $f(u_0 | \mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n)$, which maximizes the global detection probability for a desired

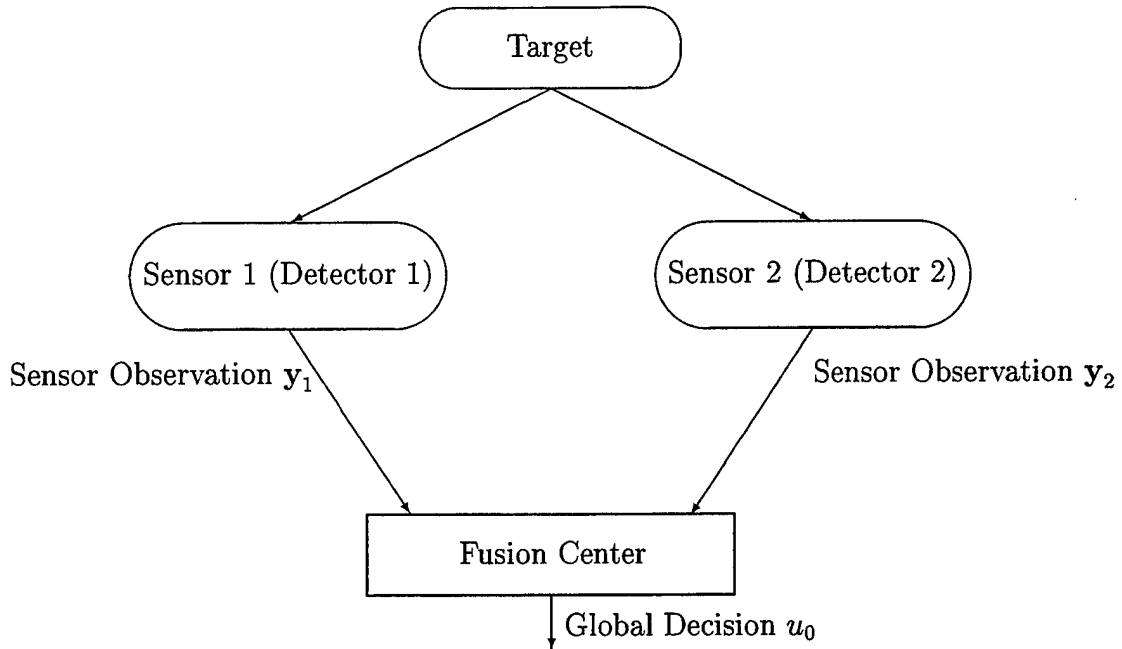


Figure 92. Centralized Detection System

global false alarm probability, where

$$p_F = P\{u_0 = 1|H_0\}, \quad (\text{VII.2})$$

$$p_D = P\{u_0 = 1|H_1\}. \quad (\text{VII.3})$$

It is well known that the solution of the centralized problem is given by a likelihood ratio test [Ref. 50]:

$$u_0 = \begin{cases} 0 & \text{if } L(\mathbf{y}_1, \dots, \mathbf{y}_n) < \lambda_0 \\ 1 & \text{if } L(\mathbf{y}_1, \dots, \mathbf{y}_n) \geq \lambda_0, \end{cases} \quad (\text{VII.4})$$

where

$$L(\mathbf{y}_1, \dots, \mathbf{y}_n) = \frac{f(\mathbf{y}_1, \dots, \mathbf{y}_n|H_1)}{f(\mathbf{y}_1, \dots, \mathbf{y}_n|H_0)}, \quad (\text{VII.5})$$

and the global decision is a hard-decision $u_0 \rightarrow \{0, 1\}$, where $u_0 = j$, for $j = 0, 1$, is interpreted as choosing H_j and the threshold λ_0 is determined according to the desired global false alarm probability.

2. Decentralized Detection Systems With Fusion

We now consider the structure of the decentralized detection system with fusion. This approach reduces the required channel capacity for two reasons: a report

of a decision is a shorter message than a sensor observation, and most sensor decisions need not be reported at all since they do not correspond to a detection. In this approach, n number of sensors receive and process the observations $\{y_i\}$ to generate n local decisions $\{u_i\}$, where $u_i = 1$ indicates target present and $u_i = 0$ indicates target absent [Ref. 47]- [Ref. 53]. These local decisions are combined into a global decision u_0 determining the presence or the absence of a target (see Figure 93). The objective is to determine the optimum sensor and fusion center architectures based on the Neyman-Pearson criterion, which requires finding an optimal fusion rule that maximizes the global detection probability for a desired global false alarm probability. The usual fusion rule is implemented as k -out of- n majority-rule voting. This means that the fusion center adopts hypothesis H_1 (presence of a target) as the true hypothesis when at least k sensors favor that hypothesis. Two special cases are *AND* fusion rule, corresponding to setting $k = n$, and *OR* fusion rule, corresponding to $k = 1$.

The optimum data fusion architecture given n sensors is developed in [Ref. 51]- [Ref. 53]. The individual decisions are weighted according to the detection and false alarm probabilities of each sensor (p_{f_i}, p_{d_i}). The optimum data fusion structure is given by

$$u_0 = \begin{cases} 0 & \text{if } \sum_{i=1}^n (c_i u_i) < \lambda_0 \\ 1 & \text{if } \sum_{i=1}^n (c_i u_i) \geq \lambda_0, \end{cases} \quad (\text{VII.6})$$

where

$$c_i = \frac{p_{d_i}(1 - p_{f_i})}{p_{f_i}(1 - p_{d_i})}, \quad (\text{VII.7})$$

and the threshold λ_0 is determined from the desired p_F .

B. OPTIMUM FUSION RULES FOR COMBINING SENSOR DECISIONS

The *AND* combiner has been analyzed by Kovattana [Ref. 47] for the case of two sensors, and the global performance has been obtained assuming that the observations are conditionally independent under hypothesis H_0 and H_1 . The *AND*

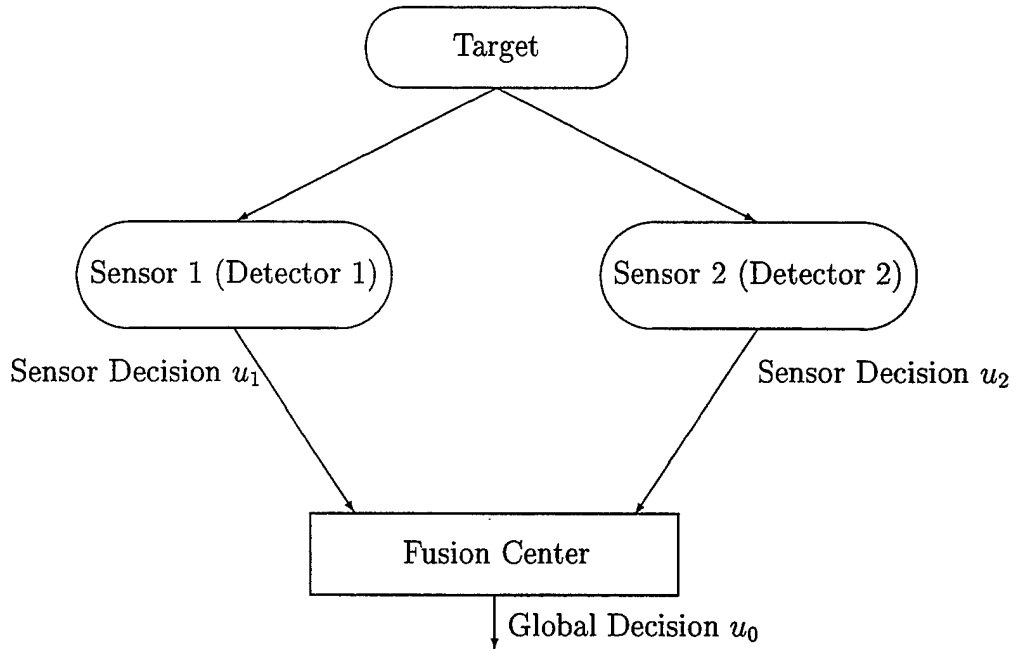


Figure 93. Decentralized Detection System With Fusion

and the *OR* combiners were later compared by Fefjar [Ref. 53] for the cases of two and three sensors. Fefjar showed that *OR* fusion rule is always superior to *AND* fusion rule. Stearns [Ref. 49] showed that depending on the choice of the global false alarm probability, either *AND* or *OR* combining can be better. Stearns [Ref. 49] claimed that the *AND* and the *OR* global performances must be intersected, *AND* is superior to *OR* at low false-alarm probabilities, and *OR* is superior to *AND* at high false-alarm probabilities (assuming Gaussian distributed observations). It will be shown that, depending on the operating point on the global receiver operating characteristic (*ROC*) and the parameters of the probability distributions under each hypothesis, either *AND* or *OR* is preferable.

1. Optimal Data Fusion Using Two Non-Identical Sensors Based on Neyman-Pearson Criterion

Consider any two sensors with receiver operating characteristics, $p_{d_1} = g(p_{f_1})$ and $p_{d_2} = h(p_{f_2})$. To derive the optimum threshold setting for each sensor, we assume that the sensor's decisions are conditionally independent under hypothesis H_0 and H_1 . In the case of *AND* fusion rule, the global false alarm and detection probabilities are

given by [Ref. 65, 73]:

$$p_F = p_{f_1} p_{f_2}, \quad (\text{VII.8})$$

$$p_D = p_{d_1} p_{d_2}. \quad (\text{VII.9})$$

Equation VII.9 can be rewritten as:

$$p_D = g(p_{f_1}) h(p_{f_2}). \quad (\text{VII.10})$$

Substituting for p_{f_2} from Equation VII.8, we obtain

$$p_D(p_F) = g(p_{f_1}) h\left(\frac{p_F}{p_{f_1}}\right), \quad (\text{VII.11})$$

where the dependence $p_D(p_F)$ is called the global *ROC* of the distributed detection system. Clearly, from Equation VII.8, $p_{f_1} > p_F$, and Equation VII.10 will be

$$p_D(p_F) = p_F < \sup_{p_{f_1} < 1} \left(g(p_{f_1}) h\left(\frac{p_F}{p_{f_1}}\right) \right). \quad (\text{VII.12})$$

In the case of *OR* fusion rule, we have

$$p_F = p_{f_1} + p_{f_2}(1 - p_{f_1}), \quad (\text{VII.13})$$

which yields

$$p_{f_2} = \frac{(p_F - p_{f_1})}{(1 - p_{f_1})}. \quad (\text{VII.14})$$

From Equation VII.13, $p_{f_1} < p_F$, and the optimum global receiver operating characteristic using an *OR* combiner is

$$0 < \sup_{p_{f_1} < p_F} \left\{ g(p_{f_1}) + h\left(\frac{p_F - p_{f_1}}{1 - p_{f_1}}\right) - g(p_{f_1}) h\left(\frac{p_F - p_{f_1}}{1 - p_{f_1}}\right) \right\}. \quad (\text{VII.15})$$

2. Optimal Data Fusion Using Identical Sensors

If the two sensors have identical receiver operating characteristics, i.e.,

$$g(p_{f_1}) = h(p_{f_2}), \quad (\text{VII.16})$$

then symmetry can be invoked to yield the following results [Ref. 64]

$$\text{AND:} \quad p_D(p_F) = g^2(\sqrt{p_F}), \quad (\text{VII.17})$$

$$\text{OR:} \quad p_D(p_F) = 2g(1 - \sqrt{1 - p_F}) - g^2(1 - \sqrt{1 - p_F}). \quad (\text{VII.18})$$

The extension of the two non-identical sensors case to the case of three or more non-identical sensors is complicated. However, the special case of n -identical sensors is straightforward. The p_F and the p_D for an n -sensor case are given by [Ref. 51]- [Ref. 53]:

$$p_F = \sum_{i=k}^n c_i^n p_f^i (1 - p_f)^{n-i}, \quad (\text{VII.19})$$

$$p_D = \sum_{i=k}^n c_i^n p_d^i (1 - p_d)^{n-i}, \quad (\text{VII.20})$$

where c_i^n is the binomial coefficient. For $k=1$, the optimum fusion rule reduces to an *OR* fusion rule, while for $k = n$ it becomes an *AND* fusion rule. For a specified value of global false alarm probability, there is an optimum integer k that maximizes the global detection probability. This is called k -out of- n fusion rule [Ref. 53, 73]. This means that if k or more sensors decide hypothesis H_1 , then the global decision will be H_1 , i.e.,

$$u_0 = \begin{cases} 0 & \text{if } \sum_{i=1}^n u_i < k \\ 1 & \text{if } \sum_{i=1}^n u_i \geq k \end{cases}, \quad (\text{VII.21})$$

where u_i , $i = 1, 2, \dots, n$, are the individual sensor decisions, and u_0 is the global decision of the fusion center.

3. Performance Optimization Examples

Stearns [Ref. 49] considered the case of combining two identical sensors with Gaussian distributed observations. His claim about the intersection of the *AND* and the *OR* combiners and the superiority of the *AND* at low false alarm probabilities and the *OR* at high false alarm probabilities is valid for the particular example which he had considered. In general, this is not true.

Here, we assume that the sensor observations are scalar quantities and exponentially distributed. The probability density functions under hypotheses H_0 and H_1 are then given by

$$f(y_i|H_0) = \begin{cases} \exp(-y_i), & y_i > 0, i = 1, 2, \dots, n \\ 0, & \text{otherwise,} \end{cases} \quad (\text{VII.22})$$

$$f(y_i|H_1) = \begin{cases} a_i \exp(-a_i y_i), & y_i > 0, i = 1, 2, \dots, n \\ 0, & \text{otherwise.} \end{cases} \quad (\text{VII.23})$$

Notice that the observations are independent when conditioned on H . The Likelihood ratio of the detectors is given by [Ref. 73, 194]:

$$L(y_i) = \frac{f(y_i|H_1)}{f(y_i|H_0)} = \frac{a_i \exp(-a_i y_i)}{\exp(-y_i)}, \quad i = 1, 2, \dots, n. \quad (\text{VII.24})$$

The decision rules of the detectors are given by:

$$u_i = \begin{cases} 0 & \text{if } L(y_i) = \frac{f(y_i|H_1)}{f(y_i|H_0)} < \lambda_i \\ 1 & \text{if } L(y_i) = \frac{f(y_i|H_1)}{f(y_i|H_0)} \geq \lambda_i, \end{cases} \quad (\text{VII.25})$$

which reduces to

$$u_i = \begin{cases} 0 & \text{if } y_i < \frac{1}{1-a_i} \ln\left(\frac{\lambda_i}{a_i}\right) \\ 1 & \text{if } y_i \geq \frac{1}{1-a_i} \ln\left(\frac{\lambda_i}{a_i}\right), \quad a_i < 1, \end{cases} \quad (\text{VII.26})$$

$$u_i = \begin{cases} 0 & \text{if } y_i \geq \frac{1}{1-a_i} \ln\left(\frac{\lambda_i}{a_i}\right) \\ 1 & \text{if } y_i < \frac{1}{1-a_i} \ln\left(\frac{\lambda_i}{a_i}\right), \quad a_i > 1, \end{cases} \quad (\text{VII.27})$$

where λ_i is the threshold of sensor i . The corresponding false alarm and detection probabilities are given by [Ref. 65, 73, 193]:

$$p_{f_i} = \left(\frac{a_i}{\lambda_i}\right)^{\left(\frac{1}{1-a_i}\right)}, \quad (\text{VII.28})$$

$$p_{d_i} = \left(\frac{a_i}{\lambda_i}\right)^{\left(\frac{a_i}{1-a_i}\right)}, \quad a_i < 1, \quad (\text{VII.29})$$

$$p_{f_i} = 1 - \left(\frac{\lambda_i}{a_i}\right)^{\frac{1}{a_i-1}}, \quad (\text{VII.30})$$

$$p_{d_i} = 1 - \left(\frac{\lambda_i}{a_i}\right)^{\frac{a_i}{a_i-1}}, \quad a_i > 1. \quad (\text{VII.31})$$

Hence the receiver operating characteristics of the detectors can be written as:

$$p_{d_i} = p_{f_i}^{a_i} = g(p_{f_i}), \quad a_i < 1, \quad (\text{VII.32})$$

$$p_{d_i} = 1 - (1 - p_{f_i})^{a_i} = h(p_{f_i}), \quad a_i > 1. \quad (\text{VII.33})$$

Figure 94 compares the receiver operating characteristics of the *OR* and the *AND* combiners as well as the individual sensor receiver operating characteristic for

two non-identical sensors with $a_1 = 0.4$ and $a_2 = 2.5$. The global performance improvement of the *OR* and the *AND* fusion rules over the individual sensor receiver operating characteristics is obvious. Figure 94 shows an intersection of the *OR* and the *AND* receiver operating characteristics. In this figure, the *AND* combiner is superior to *OR* at low global false alarm probability and the *OR* combiner is superior to *AND* at high global false alarm probability. The choice between them is determined by the specified global false alarm probability.

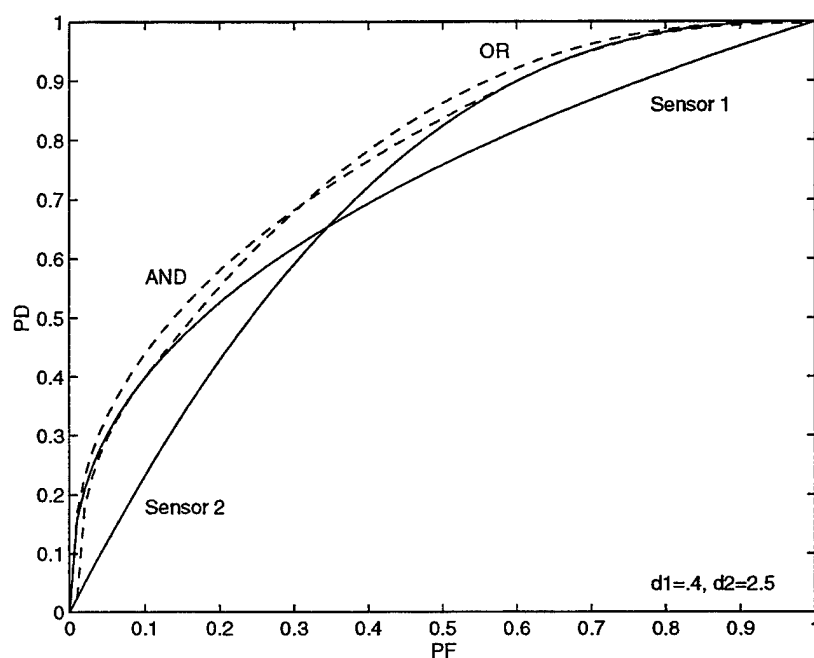


Figure 94. Comparison of *ROC*s of Two Different Sensors, $a_1=0.4$, $a_2=2.5$.

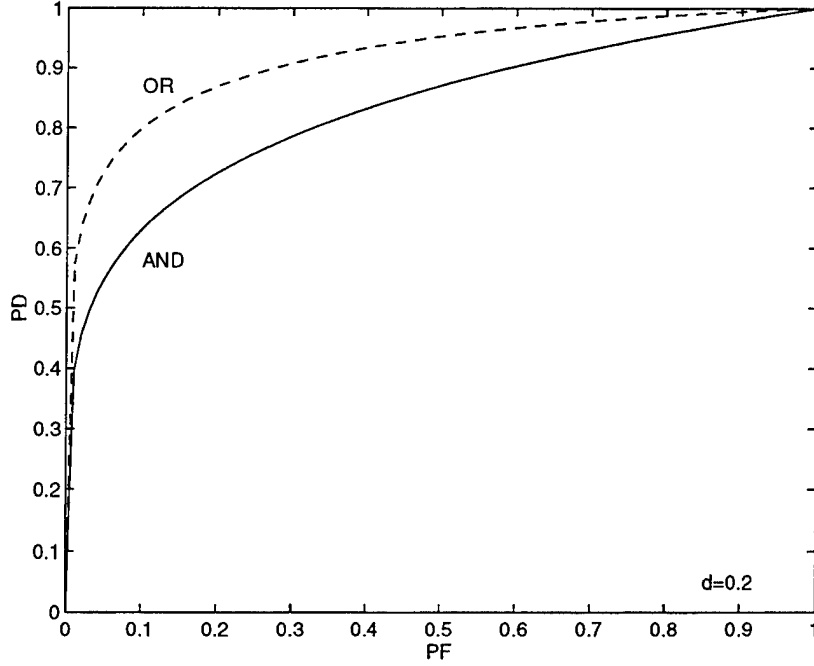


Figure 95. Comparison of *ROC*s of Two Identical Sensors, Coefficient $a = 0.2$

A comparison of the *OR* and the *AND* combiners for the case of two identical sensors with exponentially distributed observations for different values of coefficient a are shown in Figures 95 - 98. Figures 95 and 97 consider the case when $a < 1$ while Figures 96 and 98 consider the case when $a > 1$. It is clear that when $a < 1$, the *OR* combiner is superior for all values of false alarm probabilities while when $a > 1$, the *AND* combiner is superior for all values of false alarm probabilities. It is also clear that there is no intersection of the *OR* and the *AND* receiver operating characteristics in these figures.

Figures 99 - 102 compare the global *ROC*s of the k - out of - n fusion rules for different values of a for the case of n -identical sensors. Figures 99 and 101 show the results for three and five identical sensors, respectively ($a < 1$). Figures 100 and 102 show the case of $a > 1$. Figures 99 - 102 lead to the same conclusions as in Figures 95 - 98

From Figures 95 - 102, it is clear that the optimum fusion rule depends only on the coefficient of the probability distributions a . It is also clear that depending on

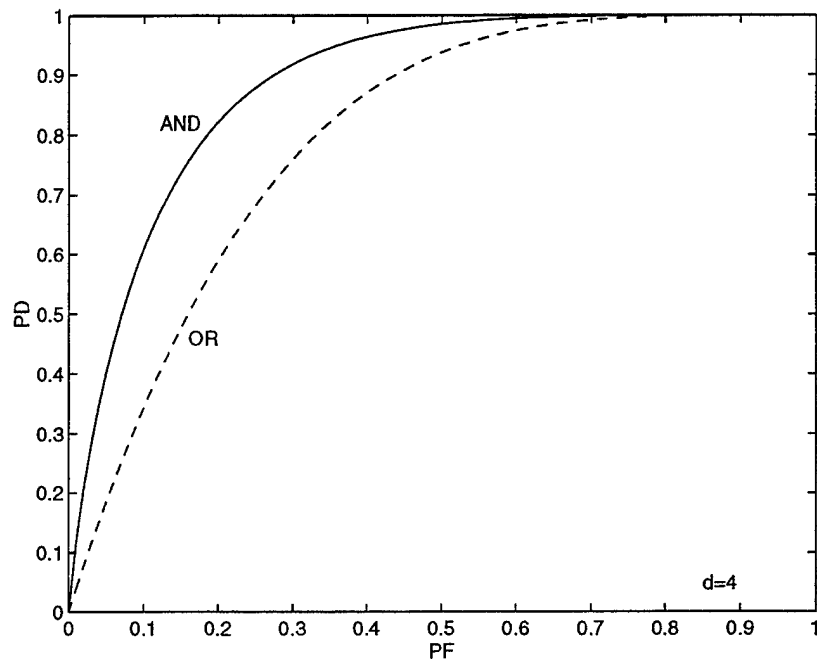


Figure 96. Comparison of *ROC*s of Two Identical Sensors, Coefficient $a = 4$

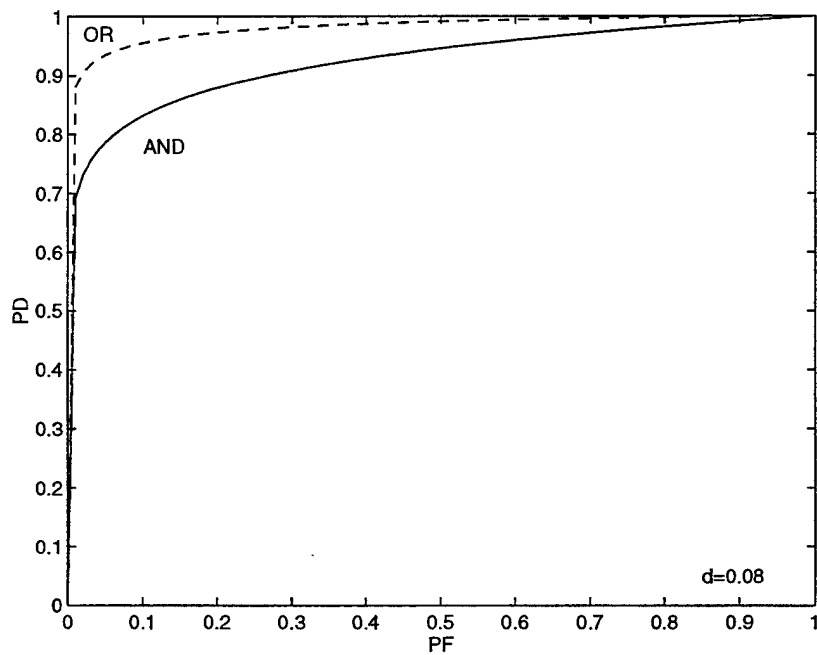


Figure 97. Comparison of *ROC*s of Two Identical Sensors, Coefficient $a = 0.08$

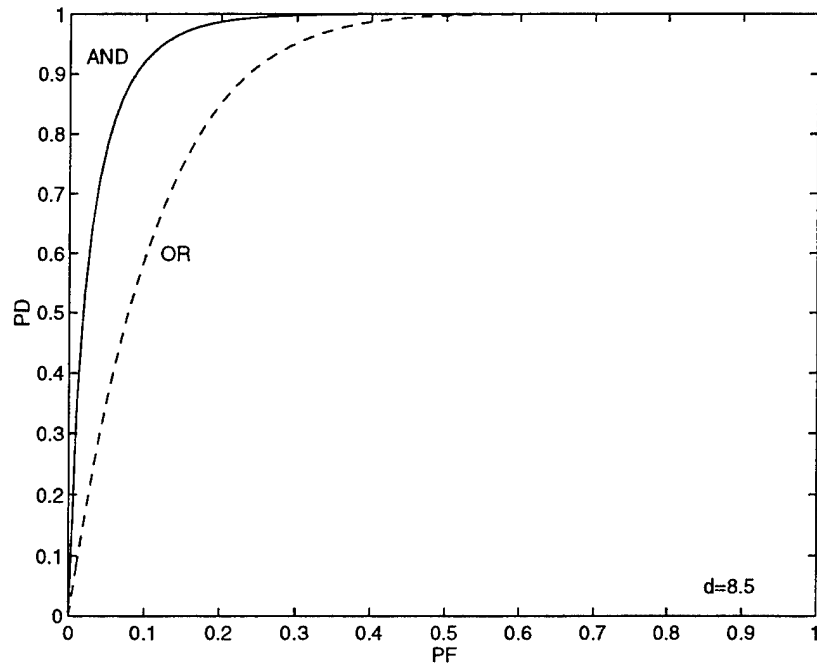


Figure 98. Comparison of *ROC*s of Two Identical Sensors, Coefficient $a = 8.5$

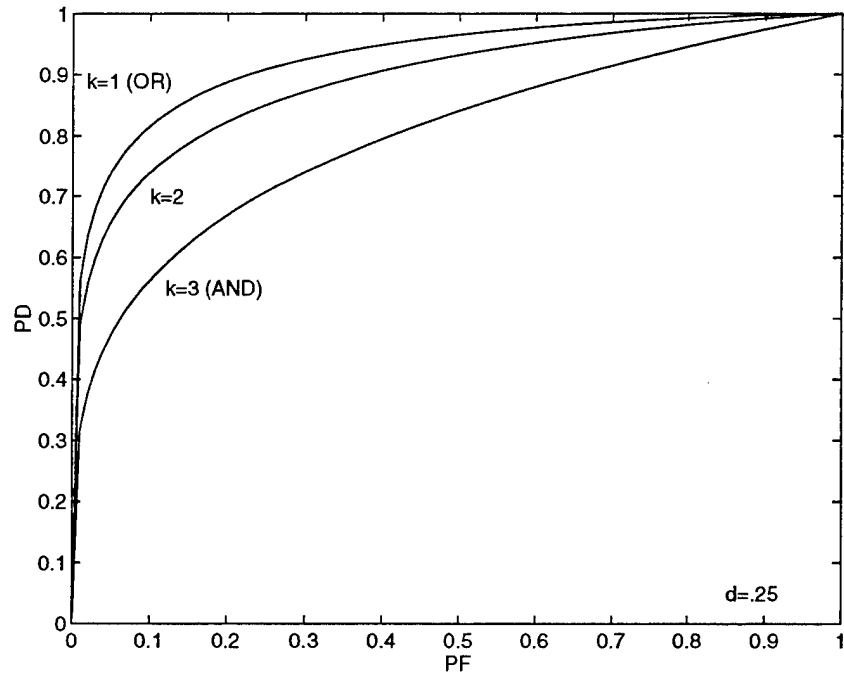


Figure 99. Comparison of *ROC*s of Three Identical Sensors, Coefficient $a = 0.25$

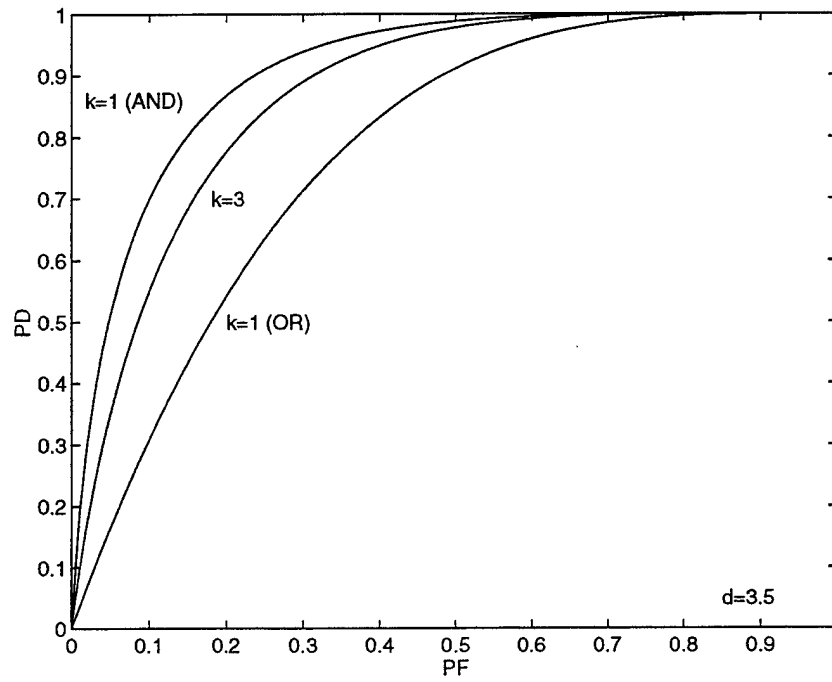


Figure 100. Comparison of *ROC*s of Three Identical Sensors, Coefficient $a = 3.5$

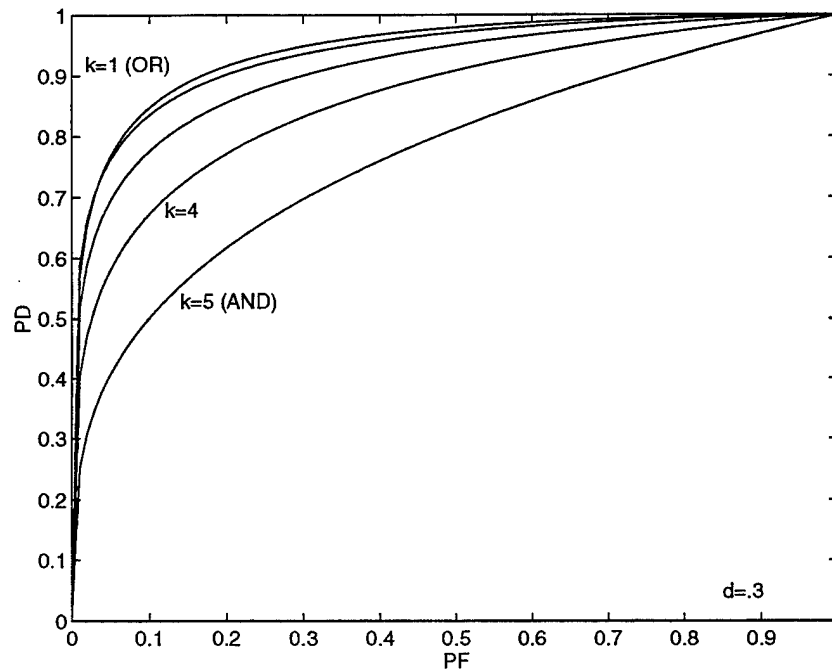


Figure 101. Comparison of *ROC*s of Five Identical Sensors, Coefficient $a = 0.3$

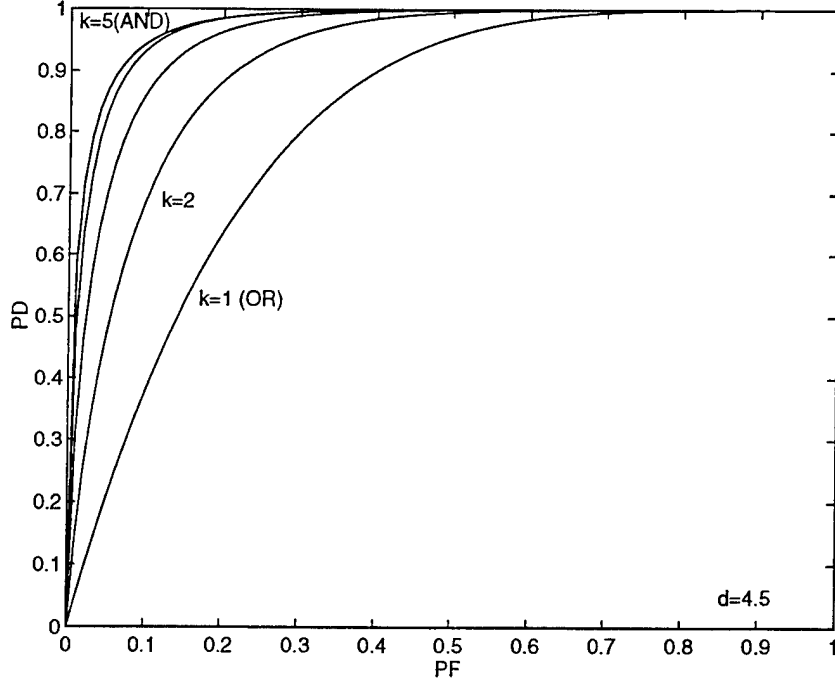


Figure 102. Comparison of *ROC*s of Five Identical Sensors, Coefficient $a = 4.5$

the coefficient a , either the *AND* or the *OR* combiner can be superior for all values of global false alarm probabilities. Furthermore, it is clear that the *ROC*s of the *OR* and the *AND* combiners may not be intersected at all. From the above results, we remark that (1) the *AND* combiner is not always superior at low p_{FS} , (2) the *OR* combiner is not always superior at high p_{FS} , (3) the choice between the *AND* and the *OR* combiners depends on the desired values of global false alarm probabilities as well as the coefficient of the probability distributions (a in our examples), and (4) the *ROC*s of the *OR* and the *AND* combiners may not be intersected at all.

C. SOFT DECISION FUSION VERSUS HARD-DECISION FUSION

Distributed detection systems employ several sensors to observe a common volume of surveillance and report local decisions about the existence or nonexistence of a target. The local decisions are reported to a data fusion processor, which is responsible for fusing the received decisions into a global decision. This approach

is called a hard-decision approach. The alternative approach is soft decision, where each sensor reports a measure of uncertainty or confidence value for each hypothesis to the data fusion processor. The soft decision approach has the advantage of better performance over a comparable hard-decision approach [Ref. 1, 53].

The hard-decision approach does not provide any information to the fusion processor for signals below the decision threshold (see Figure 104). Thus the information at lower signal levels is lost, and there is no integration of data in this case. In contrast, the soft decision approach allows the sensors to report a measure of uncertainty or confidence value for each hypothesis, at any sensor signal level. The data fusion processor can thus integrate these values over a wide range of signal levels. The soft decision approach is shown to reduce the performance loss between the centralized and the decentralized approaches [Ref. 1].

Several studies have been reported on the fusion of hard and soft sensor decisions. Tenney and Sandell [Ref. 50] made the pioneering effort in extending the Bayesian decision theory to the case of multisensor distributed detection systems. Chair et al. [Ref. 51] derived the optimum data fusion structure that minimizes the overall probability of error. Thomopoulos et al [Ref. 53] derived the optimum fusion rule for the fusion of hard and semisoft decisions using Neyman Pearson criterion. Waltz [Ref. 1] showed that the soft-decision has provided time and range improvements over a comparable hard-decision system. ElAyadi and Ashraf Mamdouh [Ref. 73] developed an algorithm for global optimization of a non-identical distributed detection system using Neyman-Pearson strategy. Al-Bassiouni [Ref. 183] considered the problem of detection using quantized discrete sensor observations. Tao and Sethi [Ref. 60] derived an optimal multiple level decision fusion strategy. Ashraf Mamdouh [Ref. 193] discussed the performance loss between the centralized and the decentralized approaches and showed that the performance loss of the decentralized approach increases as either the number of sensors or the signal to noise ratio increases.

A soft decision approach based on fuzzy logic techniques is proposed in this

section. The proposed fuzzy decision approach does not require prior statistical knowledge of the sensing process [Ref. 1, 2, 53]. In this section, the optimum fusion rule using the proposed soft decision approach is derived based on Neyman-Pearson criterion. The performance of the proposed approach is evaluated and compared to that of the hard-decision approach using an example of five identical distributed sensors with Gaussian distributed observations under hypothesis H_0 and H_1 . The proposed approach provides detection probability improvement over a comparable hard-decision system; thus, it reduces the performance loss between the centralized and the decentralized (hard-decision) approaches.

1. Proposed Fuzzy Logic Decision Approach

We consider n detectors with statistically independent observations \mathbf{y}_i , $i = 1, \dots, n$. The hard-decision rules of the individual detectors are given by [Ref. 52, 65, 73]

$$u_i = \begin{cases} 0 & \text{if } L(\mathbf{y}_i) = \frac{f(\mathbf{y}_i|H_1)}{f(\mathbf{y}_i|H_0)} < \lambda_i \\ 1 & \text{if } L(\mathbf{y}_i) = \frac{f(\mathbf{y}_i|H_1)}{f(\mathbf{y}_i|H_0)} \geq \lambda_i, i = 1, 2, \dots, n, \end{cases} \quad (\text{VII.34})$$

where $L(\mathbf{y}_i)$ is the Likelihood ratio of the i^{th} sensor, $f(\mathbf{y}_i|H_j)$ is the conditional probability density function of the i^{th} sensor observation given hypotheses H_j , $j = 0, 1$, and λ_i is the i^{th} detector threshold. Each sensor then derives a soft decision μ_i by defining a fuzzy set A_i in Y as a set of ordered pairs:

$$A_i = \{(y, \mu_{A_i}(y)) \mid y \in Y\}, i = 1, 2, \dots, n, \quad (\text{VII.35})$$

where $\mu_{A_i}(y)$ is the grade of membership of y in A_i which maps Y to the interval $[0, 1]$. If $\mu_{A_i}(y)$ is greater than 0.5, the sensor will favor hypotheses H_1 , and the corresponding hard-decision will be $u_i = 1$. If $\mu_{A_i}(y)$ is less than 0.5, the sensor is more likely to favor hypotheses H_0 , and the corresponding hard-decision is $u_i = 0$. Thus the relation between the hard-decision u_i and the soft decision μ_i is given by

$$u_i = \begin{cases} 1 & \text{if } \mu_i \geq 0.5 \\ 0 & \text{if } \mu_i < 0.5. \end{cases} \quad (\text{VII.36})$$

In many cases, it is desirable to express the membership in terms of a function with adjustable parameters. Here we propose two heuristics to achieve this objective: as the difference between the Likelihood function and the threshold increases, the corresponding membership grade of the decision increases and vice versa; if the Likelihood function is equal to the threshold, a suitable membership value is 0.5. According to these heuristics, the desired membership function can be defined as [Ref. 38]:

$$\mu_A(x; \alpha, \lambda, \gamma) = \begin{cases} 0 & \text{if } x \leq \alpha \\ 2\left[\frac{x-\alpha}{\gamma-\alpha}\right]^2 & \text{if } \alpha \leq x \leq \lambda \\ 1 - 2\left[\frac{x-\gamma}{\gamma-\alpha}\right]^2 & \text{if } \lambda \leq x \leq \gamma \\ 1 & \text{if } x \geq \gamma, \end{cases} \quad (\text{VII.37})$$

where x represents the likelihood ratio, λ represents the sensor threshold, and the actual values of γ and α depend on the expected signal range under hypothesis H_0 and H_1 . The resulting membership function is plotted in Figure 105 assuming $\alpha = 3$, $\lambda = 6$, and $\gamma = 9$.

Let $\mathbf{u} = (u_1, u_2, \dots, u_n)$ be a vector of the hard-decisions. The Likelihood function of the sensor decisions is given by

$$L(\mathbf{u}) = \frac{f(\mathbf{u}|H_1)}{f(\mathbf{u}|H_0)} = \frac{f(u_1, u_2, \dots, u_n|H_1)}{f(u_1, u_2, \dots, u_n|H_0)}. \quad (\text{VII.38})$$

Assuming that the observations are independent, we can write

$$L(\mathbf{u}) = \frac{f(\mathbf{u}|H_1)}{f(\mathbf{u}|H_0)} = \prod_{i=1}^n \frac{f(u_i|H_1)}{f(u_i|H_0)}. \quad (\text{VII.39})$$

Equivalently, we can write

$$f(\mathbf{u}|H_1) = \prod_{S+} f(u_i = 1|H_1) \prod_{S-} f(u_i = 0|H_1), \quad (\text{VII.40})$$

$$f(\mathbf{u}|H_0) = \prod_{S+} f(u_i = 1|H_0) \prod_{S-} f(u_i = 0|H_0), \quad (\text{VII.41})$$

where $S+$ is the set of all i such that $u_i = 1$ or $\mu_i \geq 0.5$, $S-$ is the set of all i such that $u_i = 0$ or $\mu_i < 0.5$, and

$$f(u_i = 1|H_1) = f(\mu_i \geq 0.5|H_1) = p_{d_i}, \quad (\text{VII.42})$$

$$f(u_i = 0|H_1) = f(\mu_i < 0.5|H_1) = 1 - p_{d_i}, \quad (\text{VII.43})$$

$$f(u_i = 1|H_0) = f(\mu_i \geq 0.5|H_0) = p_{f_i}, \quad (\text{VII.44})$$

$$f(u_i = 0|H_0) = f(\mu_i < 0.5|H_0) = 1 - p_{f_i}, \quad (\text{VII.45})$$

and p_{f_i} and p_{d_i} are the false alarm and the detection probabilities of the i^{th} sensor, respectively. The corresponding log likelihood ratio test is

$$\log(L(\mathbf{u})) = \sum_{S+} \log \frac{p_{d_i}}{p_{f_i}} + \sum_{S-} \log \frac{1 - p_{d_i}}{1 - p_{f_i}}. \quad (\text{VII.46})$$

Therefore, the data fusion rule can be expressed as

$$u_0 = \begin{cases} 0 & \text{if } \sum_{i=1}^n b_i \mu_i < \log \lambda_0 \\ 1 & \text{if } \sum_{i=1}^n b_i \mu_i \geq \log \lambda_0, \end{cases} \quad (\text{VII.47})$$

where $\log \lambda_0$ is determined according to the desired false alarm probability, and the optimum coefficients $b_i, i = 1, 2, \dots, n$, are given by

$$b_i = \begin{cases} \log \frac{p_{d_i}}{p_{f_i}} & \text{if } \mu_i \geq 0.5 \\ \log \frac{1 - p_{d_i}}{1 - p_{f_i}} & \text{if } \mu_i < 0.5. \end{cases} \quad (\text{VII.48})$$

2. Performance Evaluation of the Proposed Approach

The sensor observations are assumed to be scalar quantities. By considering n -identical sensors with Gaussian distributed observations, we have

$$\begin{aligned} f(y_i|H_1) &= \frac{1}{\sqrt{2\pi}} e^{-(y_i - s_i)^2/2}, \quad s_i > 0, \\ f(y_i|H_0) &= \frac{1}{\sqrt{2\pi}} e^{(y_i)^2/2}, \quad i = 1, 2, \dots, n, \end{aligned} \quad (\text{VII.49})$$

where s_i is the mean value under hypothesis H_1 . Consequently, Neyman-Pearson test, utilizing all of the received observations $\{y_i\}$ in a centralized detection system, has the form [Ref. 65]

$$u_0 = \begin{cases} 0 & \text{if } \sum_{i=1}^n y_i < \lambda_0 \\ 1 & \text{if } \sum_{i=1}^n y_i \geq \lambda_0. \end{cases} \quad (\text{VII.50})$$

To achieve the desired global false alarm probability, a threshold of

$$\lambda_0 = \sqrt{n} \phi^{-1}(p_F) , \quad (\text{VII.51})$$

is needed, where the complimentary error function

$$\phi(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-\frac{z^2}{2}} dz . \quad (\text{VII.52})$$

The corresponding global detection probability is given by

$$p_D = \phi \left(\frac{\lambda_0 - ns}{\sqrt{n}} \right) . \quad (\text{VII.53})$$

The decision rules of the sensors for the decentralized detection systems are given by [Ref. 65]

$$u_i = \begin{cases} 0 & \text{if } L(y_i) = \frac{f(y_i|H_1)}{f(y_i|H_0)} < \lambda_i \\ 1 & \text{if } L(y_i) = \frac{f(y_i|H_1)}{f(y_i|H_0)} \geq \lambda_i . \end{cases} \quad (\text{VII.54})$$

The corresponding false alarm and detection probabilities are

$$\begin{aligned} p_{f_i} &= \phi(\lambda_i) , \\ p_{d_i} &= \phi(\lambda_i - s_i) , \end{aligned} \quad (\text{VII.55})$$

where λ_i is the i^{th} detector threshold and is determined according to the sensor false alarm probabilities [Ref. 53, 65, 73, 194]. The signal to noise ratio (SNR) at each sensor is evaluated as

$$SNR = \frac{(E\{y_i|H_1\} - E\{y_i|H_0\})^2}{Var\{y_i|H_0\}} = s_i^2 , i = 1, \dots, n. \quad (\text{VII.56})$$

3. Simulation

Equation VII.37 is considered to determine the membership values in the simulation. The parameter $\lambda = (\alpha + \gamma)/2$ is the crossover point. The values of α and γ are chosen to be 3σ points of the Gaussian distribution, i.e.,

$$\alpha = \lambda - 3\sigma , \quad (\text{VII.57})$$

$$\gamma = \lambda + 3\sigma , \quad (\text{VII.58})$$

where σ is the standard deviation of the noise under hypothesis H_0 .

Membership values in the interval $[0, 1]$ are divided into N_q number of quantization levels of uniform step size ϵ . If the value of the membership grade μ falls within the j^{th} quantization interval, then the quantized value of μ is taken to be the midpoint of that interval. The step size ϵ is $\frac{1}{N_q}$.

The transfer characteristic of the quantizer used to generate the quantized membership grade μ_q is shown in Figure 103. The quantized steps are given by

$$\mu_{qj} = \left(\frac{2j - 1}{2} \right) \epsilon, \text{ for } j = 1, 2, \dots, N_q. \quad (\text{VII.59})$$

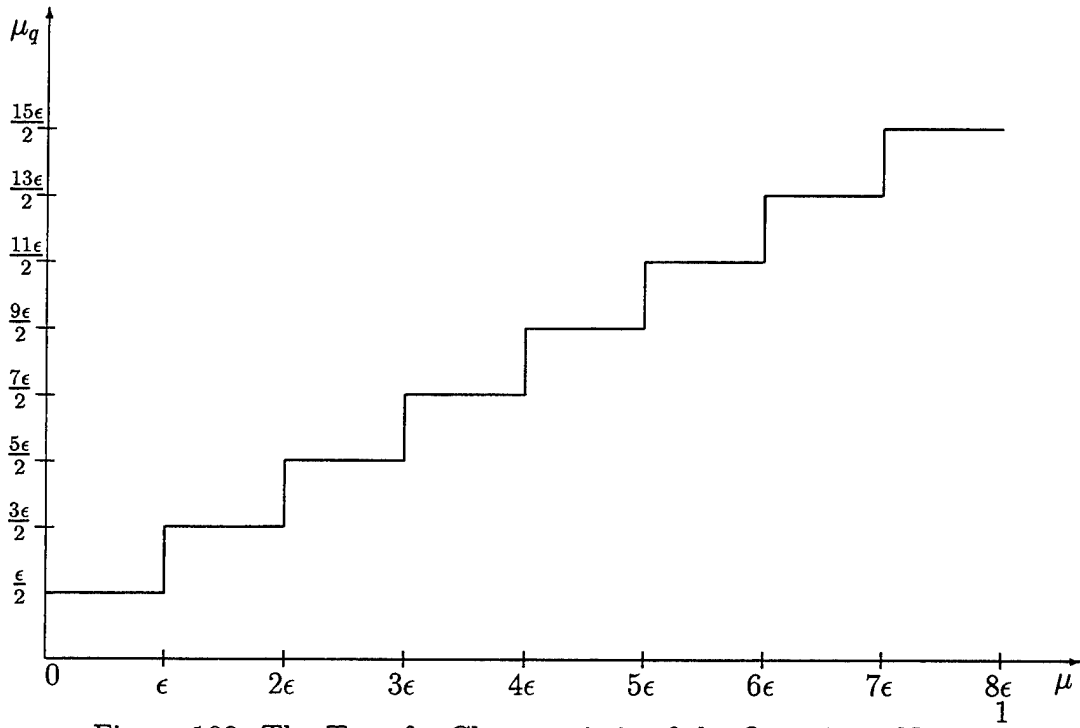


Figure 103. The Transfer Characteristic of the Quantizer, $N_q = 8$

The *ROC* plots in Figure 106 compare the global performance of the centralized, the decentralized, and the soft (fuzzy) decision schemes for $N_q = 16$ and five identical sensors with Gaussian distributed observations having a signal to noise ratio of 0 dB . Figure 106 also shows the individual sensor *ROC*. The performance improvement of data fusion systems (centralized, decentralized, or soft decision) over the individual sensor *ROC* is obvious. The performance loss due to the decentralized approach compared to the centralized approach is also illustrated. It is clear that the proposed fuzzy decision approach with $N_q = 16$ has better performance than the hard-decision approach. Thus the fuzzy decision approach reduces the performance loss between the centralized and the decentralized approaches. Figure 107 depicts the *ROC* plots of the proposed soft decision approach for different quantization levels. As shown in Figure 107, the performance of the soft decision approach is improved as the number of quantization levels increases. This result is expected since the soft decision approach utilizes more information from the underlying process as the number of quantization levels increases. Thus the performance trade-off among centralized, decentralized, and soft decision approaches can be quantified in terms of the communication bandwidth required for transmitting sensor information to the fusion center. It is worth noting that low data transmission rates lead to low cost, immunity to jamming, and longer communication range.

Optimum fusion rules for multiple sensor distributed detection systems have been considered in this chapter. For the case of exponentially distributed observations, the optimal fusion rule is based on the value of the coefficient of the probability distribution (a). For $a < 1$, the *OR* fusion rule is found to be optimal whereas the *AND* fusion rule is optimal for $a > 1$. The choice between them depends on the desired global false alarm probability as well as the parameters of the probability distributions under both hypotheses. Furthermore, the global receiver operating characteristics of the *OR* and the *AND* combiners may or may not intersect depending on the coefficients of the probability distribution function.

A fuzzy decision approach for multisensor distributed detection systems has

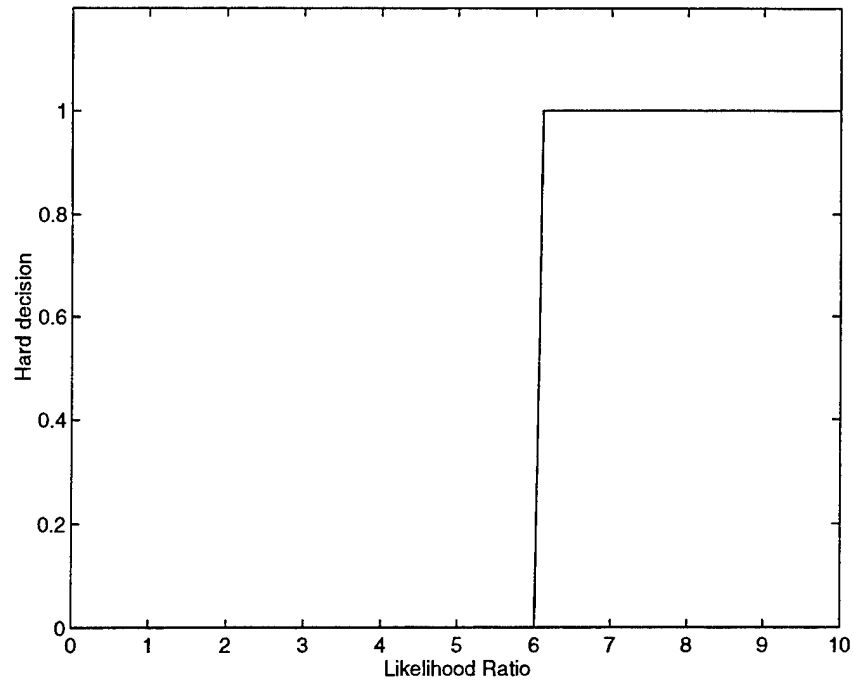


Figure 104. Plot of Hard-Decision Versus Likelihood Ratio

been proposed. The proposed soft decision approach provides an improvement in the detection probability over a comparable hard-decision approach. Using simulation results, it has been shown that the proposed fuzzy decision approach reduces the performance loss between the centralized and the decentralized approaches. This result is important, since it characterizes the performance trade-off between the centralized, decentralized, and soft decision approaches.

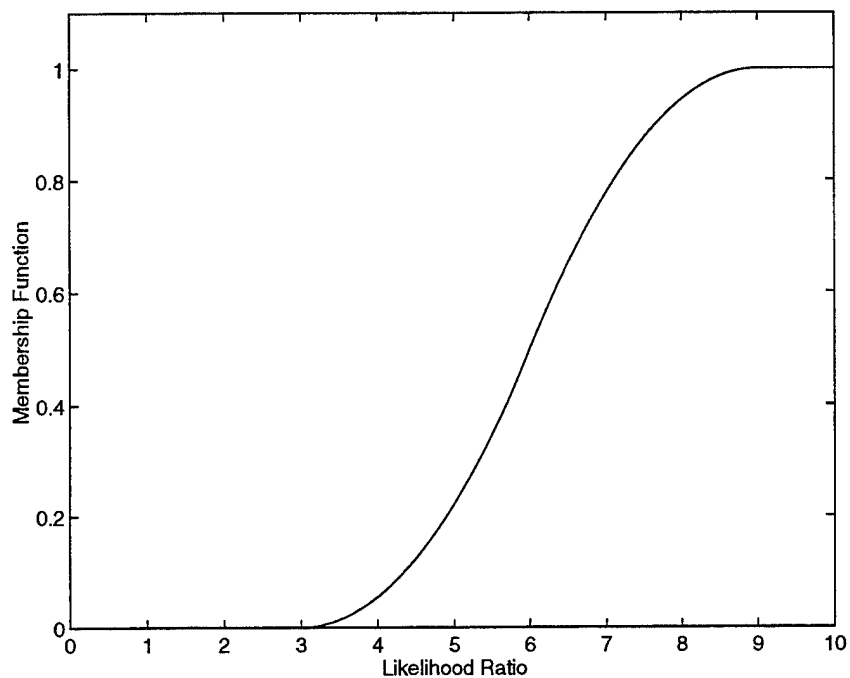


Figure 105. Plot of Membership Function Versus Likelihood Ratio

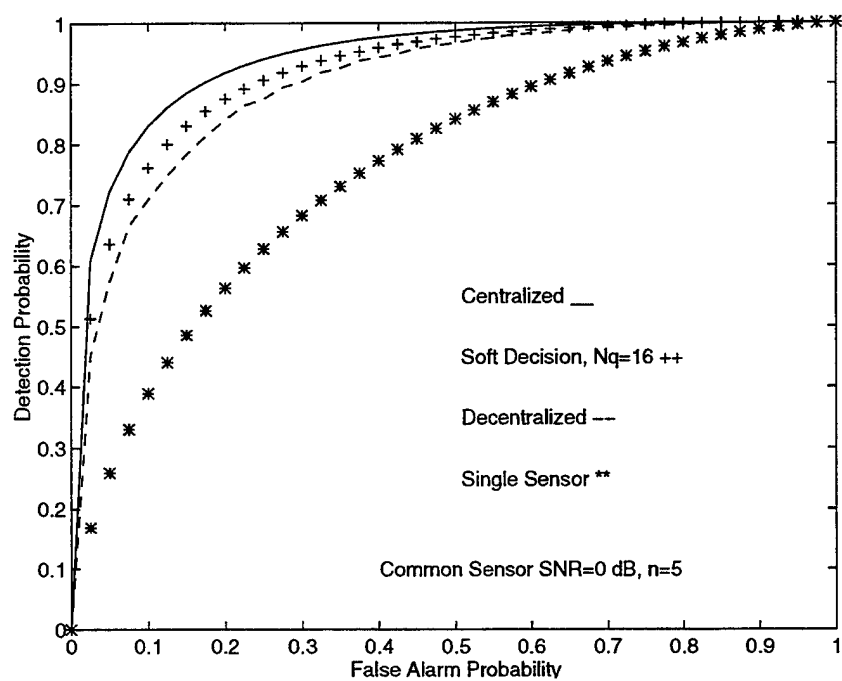


Figure 106. Centralized, Decentralized, Soft Decision ($N_q = 16$), and Single Sensor ROC's

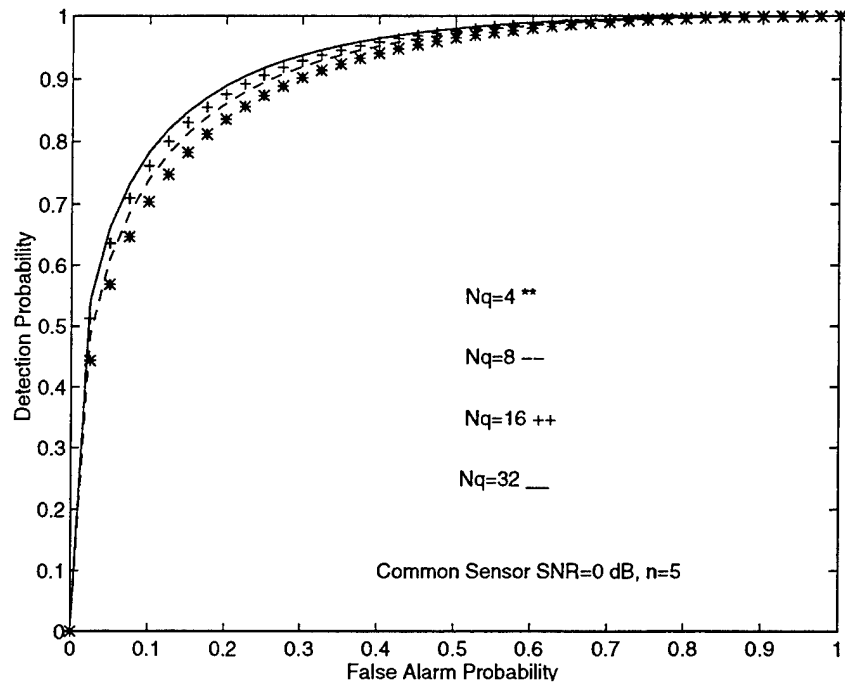


Figure 107. Soft Decision ROC's for Different Values of Quantization Levels, $N_q = 4, 8, 16, 32$

VIII. CONCLUSIONS

A. SUMMARY OF WORK

In multisensor data fusion, data from multiple sensor systems are combined to improve performance and reliability of target detection and tracking. This topic has received considerable attention in the past few years in both military and civilian applications.

The research presented in this dissertation has focused on the use of fuzzy techniques to solve the problems of measurement-to-track association, track-to-track-association, track fusion, and decision fusion in distributed multisensor-multitarget (*MSMT*) environments with overlapping sensor coverage. Four major contributions to the field of multisensor data fusion have been made in this dissertation as listed below.

(1) A technique for nearest-neighbor fuzzy measurement-to-track association has been proposed. This approach is based on the fuzzy clustering means algorithm and is suitable for sensors having different types of attributes. Unlike other fuzzy measurement-to-track association approaches reported in the literature [Ref. 58], which use membership functions based on heuristic rules, the proposed approach determines the membership functions directly from the data, which are easy to implement and reasonably robust. The main advantages of the proposed approach are simplicity and scalability in the sense that it can be extended to large number of targets without performance degradation. Monte Carlo simulations have been conducted to evaluate and compare the performance of the proposed approach with other fuzzy approaches [Ref. 58]. In terms of performance and computational complexity, the results compare favorably to other approaches. For example, the approach of Singh and Bailey [Ref. 58] performed 80% perfect correlation for the case of two crossing targets with certain noise levels while the proposed approach performed 100% for the same example. Furthermore, using the conventional fuzzy association techniques, the required computations to associate six observations to six targets, assuming three

attributes and five linguistic variables, is of the order of 2×10^7 *IF THEN* rules while the proposed approach requires the computation of a similarity matrix of dimension 6×6 to solve the same problem. The results enable us to conclude that the proposed approach performs better and requires fewer computations than the existing fuzzy measurements-to-track association techniques.

(2) A new all-neighbor fuzzy data association approach has been developed. Based on extensive literature search, this is the first all-neighbor fuzzy measurement-to-track association approach reported in the literature. Unlike other fuzzy data association techniques which assign only one observation to each existing track according to a suitable similarity measure, the proposed approach incorporates all observations to update the state estimate of an existing track. The membership functions are computed on the basis of the innovations. Monte Carlo simulations have been conducted on tracking problems with four attributes, and the performance has been compared to that of the nearest-neighbor standard filter. The results showed the effectiveness of the proposed all-neighbor association approach and the feasibility of using fuzzy logic techniques in all-neighbor association. The results are preliminary but encouraging.

(3) A novel fuzzy clustering approach, employing track-to-track association, and a fuzzy superclustering approach, employing track fusion, in multisensor-multitarget multiple-attribute environment with overlapping sensor coverage has been proposed. Unlike fuzzy track-to-track association techniques in which the membership functions are chosen heuristically, data adaptive membership functions are generated using the fuzzy clustering means algorithm in the proposed approach.

Global association decisions based on the fusion of different association rules have been proposed. A new fuzzy track-to-track association rule based on the concept of the cross-resolution has also been proposed. Fuzzy track-to-track association and track of different dimensionality estimates have been addressed. Different track-to-track association techniques, including classical techniques, are compared in terms of association accuracy. Application of the proposed fuzzy approach in over-the-horizon radar is also presented. Computer simulations together with applications to marine

traffic data obtained from the United States Coast Guard Vessel Traffic Services System demonstrate the effectiveness of the proposed approach. In some cases, it has been shown that the fused track may be less accurate than the most accurate track. This is the case when the sensor accuracies vary widely. Another advantage of the proposed track-to-track association approach is that, by assigning a degree of membership to each attribute, it reduces the computational complexity by a factor of n_a , where n_a is the total number of attributes. It also reduces the sensitivity of the fuzzy association decision to individual attribute fluctuations. When the sensor accuracies vary widely, the superior track is determined automatically on the basis of sensor resolutions and the estimated tracks. The proposed clustering technique can treat the tracks either pairwise or all at once in order to reduce the conflict situations.

(4) Optimum fusion rules for combining sensor decisions in multiple-sensor distributed detection systems have been investigated. For the case of exponentially distributed observations, depending on the operating point on the global receiver operating characteristic and on the parameter of the exponential distribution, it has been shown that the suitable fusion rule is an *AND* or an *OR* combiner for a low or a high global false alarm probability, respectively. Furthermore, receiver operating characteristics of the *AND* and the *OR* combiners may not intersect at all. A fuzzy (soft) decision approach for multisensor distributed detection systems has been proposed. The proposed approach does not require prior statistical knowledge of the sensing process. An optimum fusion rule using the proposed fuzzy decision approach is derived based on the Neyman-Pearson criterion, which maximizes the global detection probability for a given global false alarm probability. Monte Carlo simulations were conducted to compare the performance of centralized, decentralized, and the proposed soft decision approaches. It has been shown that the proposed approach yields an improved detection probability over a comparable hard-decision system, thus reducing the performance loss between the centralized and the decentralized approaches. This result characterizes performance trade-off between the centralized, decentralized, and soft decision approaches in terms of the detection performance and

the communication bandwidth requirements.

B. SUGGESTIONS FOR FUTURE RESEARCH

For future research and extensions of the work undertaken in this dissertation, the following suggestions are made.

Software implementation of track-to-track association and track fusion algorithms to associate and fuse tracks in real time for practical distributed multisensor-multitarget environments, such as distributed multisensor multi-vessel scenarios in the harbors and waterways, distributed multisensor multi-vehicle scenarios in the battlefield and distributed multisensor multi-aircraft scenarios in the space, may be considered.

Development of fuzzy techniques for measurement-to-measurement association for track initiation, track confirmation, and track deletion is an important extension. A track is initiated when an observation is not assigned to any of the existing tracks. A track is confirmed when successive observations are associated to the same initiated track. A track is deleted based on consecutive misses of observations.

Development of fuzzy clustering and superclustering techniques to solve the problems of track-to-track association and track fusion in case of multisensor-multitarget environment with clutter environment is of interest. The relation between the membership functions and the clutter models should also be addressed.

The problem of identity fusion, which is the last function of Level 1 processing in the data fusion model, needs to be addressed. Identity fusion seeks to fuse identity information about the observed targets. Identity fusion requires classification of targets (e.g., the type of aircraft).

Techniques for optimal assignment of observations to tracks for the proposed data association approach presented in Chapter IV need to be developed. The proposed approach in Chapter IV, assigns observations into tracks in a sequential nearest-neighbor association. However, the performance of the proposed approach can be further improved by choosing an assignment between observations and tracks that

maximizes the sum of the degrees of membership.

Detailed analysis of the effect of the fuzzification constant, m , of the fuzzy clustering means algorithm on track-to-track association and track fusion for different sensor accuracies in different scenarios and applications is an important problem. This analysis must be carried out for each individual attribute.

APPENDIX A. REVIEW OF KALMAN FILTER EQUATIONS

The Kalman filter is a recursive least squares estimator in discrete time dynamic systems [Ref. 78, 84]. The target motion model is assumed to be

$$\mathbf{x}(k+1) = \mathbf{F} \mathbf{x}(k) + \mathbf{G}(k) \mathbf{u}(k) + \mathbf{g}(k), \quad (\text{A.1})$$

where $\mathbf{x}(k)$ is an n dimensional state vector at time instant k , \mathbf{F} is a state transition matrix, $\mathbf{G}(k)$ is a constant matrix sequence, $\mathbf{u}(k)$ is a deterministic input, and $\mathbf{g}(k)$ is a noise input sequence (plant noise). The measurement equation is modeled as

$$\mathbf{y}(k) = \mathbf{H}(k) \mathbf{x}(k) + \mathbf{w}(k), \quad (\text{A.2})$$

where $\mathbf{y}(k)$ is an M dimensional measurement vector, $\mathbf{H}(k)$ is an $M \times n$ measurement matrix, and $\mathbf{w}(k)$ is a measurement noise sequence. The plant noise and the measurement noise sequences are assumed to be uncorrelated zero mean Gaussian sequences with the following covariance structure

$$\mathbf{Q}(k) = \text{Cov}(\mathbf{g}(k)), \quad (\text{A.3})$$

$$\mathbf{C}(k) = \text{Cov}(\mathbf{w}(k)) \quad (\text{A.4})$$

The state vector \mathbf{x} is the quantity to be estimated such that the estimation mean-squared error is minimum. The estimation error vector is defined as

$$\mathbf{e}(k) = E\{[\mathbf{x}(k) - \hat{\mathbf{x}}(k)][\mathbf{x}(k) - \hat{\mathbf{x}}(k)]'\}, \quad (\text{A.5})$$

where $\hat{\mathbf{x}}$ is an estimate of \mathbf{x} . The weighted least squares estimate and the covariance matrix are predicted at the next measurement time as follows

$$\hat{\mathbf{x}}(k+1 | k) = \mathbf{F}(k) \hat{\mathbf{x}}(k | k) + \mathbf{G}(k) \mathbf{u}(k), \quad (\text{A.6})$$

$$\mathbf{P}(k+1 | k) = \mathbf{F}(k) \mathbf{P}(k | k) \mathbf{F}'(k) + \mathbf{Q}_k. \quad (\text{A.7})$$

The estimate and the covariance matrix are then updated based on the new measurement:

$$\hat{\mathbf{x}}(k+1 | k+1) = \hat{\mathbf{x}}(k+1 | k) + \mathbf{K}(k+1) \tilde{\mathbf{y}}(k+1), \quad (\text{A.8})$$

$$\mathbf{P}(k+1 | k+1) = [\mathbf{I} - \mathbf{K}(k+1)\mathbf{H}(k+1)]\mathbf{P}(k+1 | k), \quad (\text{A.9})$$

where the Kalman filter gain $\mathbf{K}(k)$ and the innovation (the residual error) $\tilde{\mathbf{y}}(k+1)$ are given by

$$\mathbf{K}(k+1) = \mathbf{P}(k+1 | k)\mathbf{H}(k+1)'[\mathbf{H}(k+1)\mathbf{P}(k+1 | k)\mathbf{H}(k+1)' + \mathbf{C}_{k+1}]^{-1}, \quad (\text{A.10})$$

$$\tilde{\mathbf{y}}(K+1) = \mathbf{y}(K+1) - \mathbf{H}(k+1)\hat{\mathbf{x}}(k+1 | k). \quad (\text{A.11})$$

The covariance matrix of the residual error is given by

$$\mathbf{S}(k+1) = \mathbf{H}(k+1)\mathbf{P}(k+1 | k)\mathbf{H}(k+1)' + \mathbf{C}_{k+1}. \quad (\text{A.12})$$

APPENDIX B. DERIVATION OF THE COVARIANCE UPDATE EQUATION IN THE PROBABILISTIC DATA ASSOCIATION FILTER

Let us denote the set of valid observations within the gate of a given target as

$$\mathbf{y}(k) = \{\mathbf{y}_i(k)\}, i = 1, 2, \dots, n_v, \quad (\text{B.1})$$

where n_v is the total number of validated observations, and the set of measurements are denoted as

$$\mathbf{y}^k = \{\mathbf{y}(j)\}, j = 1, 2, \dots, k, \quad (\text{B.2})$$

where k represents the index of the time interval. The state estimate is assumed to be Gaussian distributed, i.e.,

$$P\{\mathbf{x}(k) \mid \mathbf{y}^{k-1}\} = N[\mathbf{x}(k); \hat{\mathbf{x}}(k \mid k-1), \mathbf{P}(k \mid k-1)]. \quad (\text{B.3})$$

We define the event that an observation is originated from the target at time k by $\theta_i(k)$, $i = 1, 2, \dots, n_v$ and the event that none of the observations at time k is originated from the target by $\theta_0(k)$ with probabilities [Ref. 7, 32, 35]

$$\beta_i(k) = P\{\theta_i(k) \mid \mathbf{y}^k\}, i = 0, 1, \dots, n_v. \quad (\text{B.4})$$

According to the previous assumptions, all these events are mutually exclusive and exhaustive, i.e.,

$$\sum_{i=0}^{n_v} \beta_i(k) = 1. \quad (\text{B.5})$$

The state update equation of the probabilistic data association filter is

$$\hat{\mathbf{x}}(k \mid k) = \hat{\mathbf{x}}(k \mid k-1) + \mathbf{W}(k)\tilde{\mathbf{y}}(k), \quad (\text{B.6})$$

where

$$\tilde{\mathbf{y}}(k) = \mathbf{y}(k) - \hat{\mathbf{y}}(k \mid k-1), \quad (\text{B.7})$$

is the combined innovation, given by

$$\tilde{\mathbf{y}}(k) = \sum_{i=0}^{n_v} \beta_i(k)(\mathbf{y}_i(k) - \hat{\mathbf{y}}_j(k | k-1)), \quad (\text{B.8})$$

where $\hat{\mathbf{y}}_j(k)$ is the predicted measurement of target j at time instant k . The covariance matrix of the state update equation is given by

$$\begin{aligned} \mathbf{P}(k | k) &= E\{[\mathbf{x}(k) - \hat{\mathbf{x}}(k | k)][\mathbf{x}(k) - \hat{\mathbf{x}}(k | k)]' | \mathbf{Y}^k\} \\ &= \sum_{i=0}^{n_v} E\{[\mathbf{x}(k) - \hat{\mathbf{x}}(k | k)][\mathbf{x}(k) - \hat{\mathbf{x}}(k | k)]' | \theta_i(k), \mathbf{Y}^k\} \beta_i(k) \\ &= \mathbf{P}_1 + \mathbf{P}_2 + \mathbf{P}_3 + \mathbf{P}_4. \end{aligned} \quad (\text{B.9})$$

The first term in Equation B.9 is

$$\begin{aligned} \mathbf{P}_1 &= \sum_{i=0}^{n_v} E\{\mathbf{x}(k)\mathbf{x}'(k) | \theta_i(k), \mathbf{Y}^k\} \beta_i(k) \\ &= \sum_{i=0}^{n_v} [E\{\hat{\mathbf{x}}_i(k | k)\hat{\mathbf{x}}_i'(k | k) + \mathbf{P}_i(k | k)\} \beta_i(k), \end{aligned} \quad (\text{B.10})$$

where

$$\mathbf{P}_i(k | k) = E\{[\mathbf{x}(k) - \hat{\mathbf{x}}_i(k | k)][\mathbf{x}(k) - \hat{\mathbf{x}}_i(k | k)]' | \theta_i(k), \mathbf{Y}^k\}. \quad (\text{B.11})$$

The conditional covariances are

$$\mathbf{P}_0(k | k) = \mathbf{P}(k | k-1) \quad (\text{B.12})$$

$$\mathbf{P}_i(k | k) = [I - \mathbf{W}(k)\mathbf{H}(k)]\mathbf{P}(k | k-1), i = 1, 2, \dots, n_v. \quad (\text{B.13})$$

From Equations B.10 - B.13, we can write

$$\mathbf{P}_1 = \beta_0(k)\mathbf{P}(k | k-1) + [1 - \beta_0(k)]\mathbf{P}(k | k) + \sum_{i=0}^{n_v} \beta_i(k)\hat{\mathbf{x}}_i(k | k)\hat{\mathbf{x}}_i'(k | k). \quad (\text{B.14})$$

The second term in Equation B.9 is

$$\begin{aligned} \mathbf{P}_2 &= -\hat{\mathbf{x}}(k | k) \sum_{i=0}^{n_v} E[\mathbf{x}'(k) | \theta_i(k), \mathbf{Y}^k] \beta_i(k) \\ &= -\hat{\mathbf{x}}(k | k)\hat{\mathbf{x}}'(k | k). \end{aligned} \quad (\text{B.15})$$

The third term, \mathbf{P}_3 , is

$$\mathbf{P}_3 = \mathbf{P}_2'. \quad (\text{B.16})$$

The last term, \mathbf{P}_4 , is

$$\begin{aligned}\mathbf{P}_4 &= \hat{\mathbf{x}}(k | k) \hat{\mathbf{x}}'(k | k) \sum_{i=0}^{n_v} \beta_i(k) \\ &= \hat{\mathbf{x}}(k | k) \hat{\mathbf{x}}'(k | k) = -\mathbf{P}_2.\end{aligned}\tag{B.17}$$

Substituting Equations B.10 and B.15 - B.17 into B.9 yields

$$\mathbf{P}(k | k) = \beta_0(k) \mathbf{P}(k | k-1) + [1 - \beta_0(k)] \mathbf{P}(k | k) + \tilde{\mathbf{P}}(k),\tag{B.18}$$

where

$$\tilde{\mathbf{P}}(k) = \sum_{i=0}^{n_v} \beta_i(k) \hat{\mathbf{x}}_i(k | k) \hat{\mathbf{x}}_i'(k | k) - \hat{\mathbf{x}}_i(k | k) \hat{\mathbf{x}}_i'(k | k).\tag{B.19}$$

From Equations III.16 - III.18, and B.19, $\tilde{\mathbf{P}}(k)$ can be rewritten as

$$\tilde{\mathbf{P}}(k) = \mathbf{W}(k) \left[\sum_{i=0}^{n_v} \beta_i(k) \tilde{\mathbf{y}}_i(k) \tilde{\mathbf{y}}_i'(k) - \tilde{\mathbf{y}}_i(k) \tilde{\mathbf{y}}_i'(k) \right] \mathbf{W}'(k),\tag{B.20}$$

where

$$\tilde{\mathbf{y}}_i(k) = \mathbf{y}_i(k) - \hat{\mathbf{y}}_j(k | k-1)\tag{B.21}$$

is the innovation due to observation i and target j at time instant k .

APPENDIX C. DERIVATION OF TRACK FUSION RELATIONSHIPS

For simplicity, we assume that we have two scalar estimates, x_1 and x_2 , such that their fused estimate is

$$x_f = x_1 + a(x_2 - x_1), \quad (\text{C.1})$$

where a is a weighting factor. The weighting factor is chosen such that the expected mean square error on the fused estimate is minimum [Ref. 3, 115]. The error of the fused estimate is defined as

$$e_{x_f} = e_{x_1} + a(e_{x_2} - e_{x_1}). \quad (\text{C.2})$$

The variance of the error is then given by

$$\sigma_e^2 = E\{e_{x_f}^2\} = \sigma_1^2 + 2a E\{e_{x_1}e_{x_2}\} - 2a\sigma_1^2 + a^2\sigma_\delta^2, \quad (\text{C.3})$$

where

$$\sigma_1^2 = E\{e_{x_1}^2\}, \quad (\text{C.4})$$

$$\sigma_2^2 = E\{e_{x_2}^2\}, \quad (\text{C.5})$$

$$\sigma_\delta^2 = E\{(e_{x_1}e_{x_2})^2\} = \sigma_1^2 + \sigma_2^2 - 2E\{e_{x_1}e_{x_2}\}. \quad (\text{C.6})$$

The cross-correlation between the two estimate errors is defined as

$$E\{e_{x_1}e_{x_2}\} \equiv P_{12}. \quad (\text{C.7})$$

Substituting Equations C.4 - C.7 into Equation C.3 yields

$$\sigma_e^2 = (1 - 2a + a^2)\sigma_1^2 + a^2\sigma_2^2 + 2(a - a^2)P_{12}. \quad (\text{C.8})$$

The optimum value of a in a mean square sense is obtained by setting

$$\frac{\partial \sigma_e^2}{\partial a} = 0, \quad (\text{C.9})$$

or

$$-2(1-a)\sigma_1^2 + 2a\sigma_2^2 + 2(1-2a)P_{12} = 0. \quad (\text{C.10})$$

The optimum value of a is then given by

$$a = \frac{\sigma_1^2 - P_{12}}{\sigma_1^2 + \sigma_2^2 - 2P_{12}}. \quad (\text{C.11})$$

Substituting Equation C.11 into Equation C.1, the fused estimate will be

$$x_f = x_1 + \frac{\sigma_1^2 - P_{12}}{\sigma_1^2 + \sigma_2^2 - 2P_{12}}(x_2 - x_1). \quad (\text{C.12})$$

In the case of zero cross-correlation between the two estimates, i.e. $P_{12} = 0$, the fused estimate reduces to

$$x_f = x_1 + \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}(x_2 - x_1) = \frac{\sigma_2^2 x_1 + \sigma_1^2 x_2}{\sigma_1^2 + \sigma_2^2}. \quad (\text{C.13})$$

The result of Equation C.13 can be easily derived for state vector estimates \mathbf{x}_1 and \mathbf{x}_2 . In this case, all variances are replaced by covariances and the weighting factor a is replaced by a weighting matrix \mathbf{A} . By replacing σ_1^2 by \mathbf{P}_1 , σ_2^2 by \mathbf{P}_2 , $2P_{12}$ by $\mathbf{P}_{12} + \mathbf{P}'_{12}$, the resulting weighting matrix is

$$\mathbf{A} = [\mathbf{P}_1 - \mathbf{P}_{12}][\mathbf{P}_1 + \mathbf{P}_2 - \mathbf{P}_{12} - \mathbf{P}'_{12}]^{-1}. \quad (\text{C.14})$$

From Equations C.8 and C.11, the error variance can be written as

$$\sigma_{x_f}^2 = \sigma_1^2 - \frac{(\sigma_1^2 - P_{12})^2}{\sigma_1^2 + \sigma_2^2 - 2P_{12}}. \quad (\text{C.15})$$

In the case of zero correlation, the resulting error variance is

$$\sigma_{x_f}^2 = \sigma_1^2 - \frac{(\sigma_1^2)^2}{\sigma_1^2 + \sigma_2^2} = \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 + \sigma_2^2}. \quad (\text{C.16})$$

For state vectors, the fused estimate and the error covariance with dependent estimation errors will be

$$\mathbf{X}_f = \hat{\mathbf{x}}_1 + (\mathbf{P}_1 - \mathbf{P}_{12})(\mathbf{P}_1 + \mathbf{P}_2 - \mathbf{P}_{12} - \mathbf{P}'_{12})^{-1}(\hat{\mathbf{x}}_2 - \hat{\mathbf{x}}_1), \quad (\text{C.17})$$

$$\mathbf{P} = \mathbf{P}_1 - (\mathbf{P}_1 - \mathbf{P}_{12})(\mathbf{P}_1 + \mathbf{P}_2 - \mathbf{P}_{12} - \mathbf{P}'_{12})^{-1}(\mathbf{P}_1 - \mathbf{P}_{12})'. \quad (\text{C.18})$$

In the case of zero cross correlation, the results are

$$\mathbf{X}_f = \mathbf{P}_2(\mathbf{P}_1 + \mathbf{P}_2)^{-1}\hat{\mathbf{x}}_1 + \mathbf{P}_1(\mathbf{P}_1 + \mathbf{P}_2)^{-1}\hat{\mathbf{x}}_2, \quad (\text{C.19})$$

$$\mathbf{P} = \mathbf{P}_1(\mathbf{P}_1 + \mathbf{P}_2)^{-1}\mathbf{P}_2. \quad (\text{C.20})$$

APPENDIX D. FUZZY SETS DEFINITIONS AND OPERATIONS

1. BASIC FUZZY SET DEFINITIONS

In fuzzy sets theory, an object x can belong to a set A with a certain degree of membership. Let X be a set of objects, called the universe, with elements $\{x\}$. For a subset A of X , define a function

$$\mu_A(x) = \begin{cases} 1, & \text{if and only if } x \in A \\ 0, & \text{if and only if } x \notin A \end{cases} \quad (\text{D.1})$$

If the function is allowed to take values in the real interval $[0, 1]$, A is called a fuzzy set, and $\mu_A(x)$ is the grade of membership of x in A . The closer the value of the degree of membership to 1, the more the element x belongs to the fuzzy set A .

The fuzzy set A is completely characterized by the set of ordered pairs

$$A = \{(x, \mu_A(x)) \mid x \in X\}, \quad (\text{D.2})$$

where $\mu_A(x)$ is the degree of membership of the element x in the fuzzy set A . The determination of the membership function $\mu_A(x)$ to which input data belong to the fuzzy set A is called fuzzification. In many cases, it is convenient to express the membership function of a fuzzy subset of the real line in terms of a standard function. The standard functions have parameters which can be adjusted to describe a specified membership function. An example of a standard membership function is the sigmoid function defined as [Ref. 39]:

$$\mu_A(x; \alpha, \beta, \gamma) = \begin{cases} 0 & \text{if } x \leq \alpha \\ 2\left[\frac{x-\alpha}{\gamma-\alpha}\right]^2 & \text{if } \alpha \leq x \leq \beta \\ 1 - 2\left[\frac{x-\gamma}{\gamma-\alpha}\right]^2 & \text{if } \beta \leq x \leq \gamma \\ 1 & \text{if } x \geq \gamma, \end{cases} \quad (\text{D.3})$$

where α, β, γ are parameters of the membership function.

When X is a finite set of n elements $\{x_1, \dots, x_n\}$, the fuzzy set A is expressed as

$$A = \mu_A(x_1)/x_1 + \mu_A(x_2)/x_2 + \dots + \mu_A(x_n)/x_n, \quad (\text{D.4})$$

or simply

$$A = \sum_{i=1}^n \mu_A(x_i)/x_i. \quad (\text{D.5})$$

When X is not finite, A is expressed as

$$A = \int_x \mu_A(x)/x, \quad (\text{D.6})$$

where \int_x denotes the union of fuzzy degrees over the universe X .

2. BASIC FUZZY OPERATIONS

For two fuzzy sets A and B , the following fuzzy set operations are defined [Ref. 81]- [Ref. 83]: Two fuzzy sets A and B are said to be equal if

$$\mu_A(x) = \mu_B(x) \quad \forall x \in X. \quad (\text{D.7})$$

The union of two fuzzy sets A and B is expressed as

$$\mu_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x)), \quad (\text{D.8})$$

where $\mu_{A \cup B}(x)$ is the membership of $A \cup B$. The intersection of two fuzzy sets A and B is expressed as

$$\mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x)), \quad (\text{D.9})$$

where $\mu_{A \cap B}(x)$ is the membership of $A \cap B$.

The complement of a fuzzy set A , denoted by \bar{A} , is defined by the membership function $\mu_{\bar{A}}(x)$, where

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x) \quad \forall x \in X. \quad (D.10)$$

A fuzzy set A is said to be included in B , i.e., $A \subseteq B$, iff

$$\mu_A(x) \leq \mu_B(x) \quad \forall x \in X. \quad (D.11)$$

The normalization of a fuzzy set, $NORM(A)$, is defined by a membership function $\mu_{NORM(A)}(x)$, where

$$\mu_{NORM(A)}(x) = \frac{\mu_A(x)}{\max\{\mu_A(x)\}} \quad \forall x \in X. \quad (D.12)$$

The dilation of a fuzzy set, $DIL(A)$, is defined by a membership function $\mu_{DIL(A)}(x)$, where

$$\mu_{DIL(A)}(x) = (\mu_A)^{0.5} \quad \forall x \in X. \quad (D.13)$$

3. FUZZY RULES

Fuzzy rules deal with linguistic variables, for example, LOW, MEDIUM, HIGH, etc. The fuzzy rules and linguistic variables are usually represented in linguistic fuzzy tables. The linguistic variables are represented by their membership functions. The fuzzy rules depend on heuristic rules and have the following general form:

IF (Features), then (Class);

or

IF (Conditions), then (Conclusions);

The heuristic rules are based on common sense and not on mathematical formulations. For example, assume that there are three class of radar, namely, Radar₁, Radar₂ and Radar₃, identified by their pulse widths (PW)

$$PW_1 = 2 \quad \mu\text{sec}$$

$$PW_2 = 6 \quad \mu\text{sec}$$

$$PW_3 = 10 \quad \mu\text{sec}.$$

A possible heuristic rule to identify the three classes is:

IF $PW \leq 4$, then Radar 1;

IF $4 < PW < 8$, then Radar 2;

IF $8 < PW$, then Radar 3;

4. DEFUZZIFICATION METHODS

Defuzzification process represents the opposite of fuzzification. It is a process of calculating a numerical value for a fuzzy variable, i.e., transformation (defuzzification) of fuzzy variables into non-fuzzy variables (crisp data). Defuzzification methods are based on heuristic rules. Two methods for defuzzification are widely used in fuzzy systems:

a. Maximum Membership Defuzzification

This method chooses the action that corresponds to the maximum degree of membership, i.e., chooses the element x_{max} that has maximal degree of membership in the output fuzzy set A :

$$\mu_A(x_{max}) = \max_{1 \leq j \leq k} \mu_A(x_j). \quad (\text{D.14})$$

If there is more than one value with maximal degree, then the mean of these values is used. In this case, the method is called the mean of maxima method. The disadvantage of this simple defuzzification method is that it ignores the information in much of the membership function.

b. Fuzzy Centroid Defuzzification

This method chooses the center of gravity or the center of the area of the membership. The center of gravity is computed as the fuzzy centroid \bar{A} defined as

$$\bar{A} = \frac{\sum_{i=1}^n x_i \mu_A(x_i)}{\sum_{i=1}^n \mu_A(x_i)}. \quad (\text{D.15})$$

Unlike the maximum membership defuzzification method, the fuzzy centroid defuzzification method uses all the information in the membership function.

APPENDIX E. DERIVATION OF FUZZY CLUSTERING MEANS ALGORITHM

Let $J_m : M_{fc} \times R^{cp} \rightarrow R^+$ be the objective function [Ref. 43]

$$J_m(\mathbf{U}, \mathbf{v}) = \sum_{k=1}^n \sum_{i=1}^c (\mu_{ik})^m (d_{ik})^2 \quad (\text{E.1})$$

where

$$U \in M_{fc} \quad (\text{E.2})$$

is a fuzzy c-partition of X , M_{fc} is a fuzzy set, and

$$\mathbf{v} = (\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_c) \in R^{cp}, \quad (\text{E.3})$$

where $\mathbf{v}_i \in R^p$ is the cluster center, c is the number of clusters, R^p is a real p dimensional vector space, and R^+ is the real interval $(0, \infty]$. The distance d is defined as any inner product induced norm on R^p , given by

$$(d_{ik})^2 = \|\mathbf{x}_k - \mathbf{v}_i\|^2, \quad (\text{E.4})$$

where m is a real number $\in [1, \infty)$ and is called the weighting exponent, and \mathbf{x}_k is a data point. Each distance between a cluster point \mathbf{x}_k and a fuzzy cluster center \mathbf{v}_i is weighted by the m^{th} power of the corresponding membership. The goal of the fuzzy clustering algorithm is to determine the optimum degrees of membership μ_{ik} ($\forall i, k$) and the optimum fuzzy cluster centers \mathbf{v}_i ($\forall i$) such that the objective function J_m is minimum [Ref. 43].

First, let \mathbf{v} be fixed. Defining $g_m(\mathbf{U}) = J_m(\mathbf{U}, \mathbf{v})$, we have

$$\min_{\mathbf{U} \in M_{fc}} \{g_m(\mathbf{U})\} = \min_{\mathbf{U} \in M_{fc}} \left\{ \sum_{k=1}^n \sum_{i=1}^c (\mu_{ik})^m (d_{ik})^2 \right\}. \quad (\text{E.5})$$

By assuming that the columns of \mathbf{U} are independent, Equation E.6 can be written as

$$\min_{\mathbf{U} \in M_{fc}} \{g_m(\mathbf{U})\} = \sum_{k=1}^n \left[\min_{\mathbf{U} \in M_{fc}} \left\{ \sum_{i=1}^c (\mu_{ik})^m (d_{ik})^2 \right\} \right]. \quad (\text{E.6})$$

It is required to minimize each term g_{mk} , defined as

$$g_{mk}(\mathbf{u}_k) = \sum_{i=1}^c (\mu_{ik})^m (d_{ik})^2, \quad (\text{E.7})$$

under the constraint

$$\sum_{i=1}^c \mu_{ik} = 1. \quad (\text{E.8})$$

Thus each g_{mk} has its Lagrangian

$$F_k(\lambda, \mathbf{u}_k) = \sum_{i=1}^c (\mu_{ik})^m (d_{ik})^2 - \lambda \left(\sum_{i=1}^c \mu_{ik} - 1 \right). \quad (\text{E.9})$$

Setting the gradient with respect to λ and μ equal to zero yields

$$\frac{\partial F_k}{\partial \lambda}(\lambda, \mathbf{u}_k) = \left(\sum_{i=1}^c \mu_{ik} - 1 \right) = 0, \quad (\text{E.10})$$

$$\frac{\partial F_k}{\partial \mu_{st}}(\lambda, \mathbf{u}_k) = [m(\mu_{st})^{m-1} (d_{st})^2 - \lambda] = 0 \quad (\text{E.11})$$

from which we can solve for

$$\mu_{st} = \left[\frac{\lambda}{m(d_{st})^2} \right]^{\frac{1}{(m-1)}}. \quad (\text{E.12})$$

Using Equation E.11, we obtain

$$\sum_{j=1}^c \mu_{jt} = \sum_{j=1}^c \left(\frac{\lambda}{m} \right)^{\frac{1}{(m-1)}} \left[\frac{1}{d_{jt}^2} \right]^{\frac{1}{(m-1)}} = \left(\frac{\lambda}{m} \right)^{\frac{1}{(m-1)}} \left\{ \sum_{j=1}^c \left[\frac{1}{d_{jt}^2} \right]^{\frac{1}{(m-1)}} \right\} = 1. \quad (\text{E.13})$$

Thus,

$$\left(\frac{\lambda}{m} \right)^{\frac{1}{(m-1)}} = \frac{1}{\sum_{j=1}^c \left(\frac{1}{d_{jt}^2} \right)^{\frac{1}{(m-1)}}}. \quad (\text{E.14})$$

From Equations E.13 and E.14, we have

$$\mu_{st} = \left\{ 1 / \sum_{j=1}^c [1/(d_{jt})^2]^{1/(m-1)} \right\} [1/(d_{st})^2]^{1/(m-1)}, \quad (\text{E.15})$$

which yields the optimal membership values

$$\mu_{st} = \frac{1}{\sum_{j=1}^c (d_{st}/d_{jt})^{2/(m-1)}}. \quad (\text{E.16})$$

Second, let U be fixed. By setting $h_m(\mathbf{v}) = j_m(\mathbf{U}, \mathbf{v})$, we have

$$h_m(\mathbf{v}) = \sum_{k=1}^n \sum_{i=1}^c (\mu_{ik})^m (d_{ik})^2 = \sum_{k=1}^n \sum_{i=1}^c (\mu_{ik})^m \langle \mathbf{x}_k - \mathbf{v}_i, \mathbf{x}_k - \mathbf{v}_i \rangle, \quad (\text{E.17})$$

where $\langle \cdot, \cdot \rangle$ is the norm-inducing inner product. Minimization of h_m is unconstrained over R^c . For all unit vectors $\mathbf{w} \in R^c$, the directional derivatives $h'_m(\mathbf{v}_i; \mathbf{w})$ is set to be equal 0, i.e.,

$$h'_m(\mathbf{v}_i; \mathbf{w}) = \sum_{k=1}^n (\mu_{ik})^m \frac{d}{dt} (\langle \mathbf{x}_k - \mathbf{v}_i - t\mathbf{w}, \mathbf{x}_k - \mathbf{v}_i - t\mathbf{w} \rangle) |_{t=0} = 0, \quad (\text{E.18})$$

i.e.,

$$-2 \left[\sum_{k=1}^n (\mu_{ik})^m \langle \mathbf{x}_k - \mathbf{v}_i, \mathbf{w} \rangle \right] = 0 = \langle \sum_{k=1}^n (\mu_{ik})^m (\mathbf{x}_k - \mathbf{v}_i), \mathbf{w} \rangle \quad \forall \mathbf{w}. \quad (\text{E.19})$$

Thus,

$$\sum_{k=1}^n (\mu_{ik})^m (\mathbf{x}_k - \mathbf{v}_i) = \mathbf{0}, \quad (\text{E.20})$$

which yields the optimal cluster centers

$$\mathbf{v}_i = \frac{\sum_{k=1}^n (\mu_{ik})^m \mathbf{x}_k}{\sum_{k=1}^n (\mu_{ik})^m} \quad \forall i. \quad (\text{E.21})$$

LIST OF REFERENCES

- [1] E. Waltz and J. Llinas, *Multisensor Data Fusion*, Norwood, MA, Artech House, 1990.
- [2] D. L. Hall, *Mathematical Techniques in Multisensor Data Fusion*, Norwood, MA, Artech House, 1992.
- [3] S. S. Blackman, *Multiple-Target Tracking With Radar Applications*, Norwood, MA, Artech House, 1986.
- [4] S. S. Iyengar, L. Prasad, and Hllmin, *Advances in Distributed Sensor Technology*, Prentice Hall, Upper Saddle River, NJ, 1995.
- [5] D. L. Hall and J. Llinas, "An Introduction to Multisensor Data Fusion," *Proceedings of the IEEE*, Vol.85, No.1, Jan. 1997, pp. 6-23.
- [6] D. L. Hall and J. Llinas, "A Survey of Techniques for CIS Data Fusion," *Proceedings of the Second International Conference on Command, Control and Computations and Management Information Systems*, Bournemouth, UK, IEEE, London, April 1987, pp. 77-84.
- [7] Y. Bar-Shalom and T. Fortman, *Tracking and Data Association*, Academic Press, 1988.
- [8] L. Martin, C. Chee-Yee, K. Ivan, A. Mark, V. Vincent, and S. Thomopoulos, "Distributed Fusion Architectures and Algorithms for Target Tracking," *Proceedings of the IEEE*, Vol.85, No.1, Jan. 1997.
- [9] J. Llinas, "Assessing the Performance of Multisensor Fusion Systems," *Proceedings of SPIE*, Vol. 1611, Sensor Fusion IV, 1991, pp. 2-27.
- [10] G.V. Trunk and J. D. Wilson, "Association of DF Bearing Measurements With Radar Track," *IEEE Transactions on Aerospace and Electronic Systems*, AES-23, No.4, July 1987, pp. 438-447.
- [11] O. Hossam, M. Farooq, and T. Quach, "Fuzzy Logic Approach to Data Association," *Proceedings of SPIE*, Vol. 2755, 1996, pp. 313-321.
- [12] J. Zhu, R. Bogner, A. Bouzerdoum, and M. Southcott, "Application of Neural Network to Track Association in Over the Horizon Radar," *Proceedings of SPIE*, Vol. 2233, 1994, pp. 224-235.
- [13] T. Fortman, Y. Bar-Shalom, and M. Scheffe, "Multi-Target Tracking Using JPDA," *Proceedings 1980 IEEE Conference on Decision and Control*, Dec. 1980, pp. 806-812.

- [14] J. Smith, "A Fuzzy Logic Multisensor Association Algorithm," *Proceedings of SPIE*, Vol. 3068, 1997, pp. 76-87.
- [15] J. Stein and S. S. Blackman, "Generalized Correlation of Multitarget Track Data," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-11, No. 6, Nov. 1975.
- [16] V. Kittur and W. E. Thompson, "Data Association Using Fused Data From Multiple Sensors," *Proceedings of SPIE*, Vol. 1699, 1992, pp. 60-71.
- [17] P. Wide and D. Driankov, "A Fuzzy Approach to Multi-Sensor Data Fusion for Quality Profile Classification," *Proceedings of IEEE/SICE/RSJ International Conference on Multisensor Fusion and Integration for Intelligent Systems*, 1996, pp. 215-221.
- [18] R. J. Fitzgerald, "Simple Tracking Filters: Position and Velocity Measurements," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-19, No.5, September 1983.
- [19] M. Wax, "Position Location from Sensors With Position Uncertainty," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-24, No.4, July 1988.
- [20] D. J. Torrieri, "Statistical Theory of Passive Location Systems," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-20, No.2, March 1984.
- [21] Y. Bar-Shalom, "Comparison of Two-Sensor Tracking Methods Based on State Vector Fusion and Measurement Fusion," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-24, No.4, July 1988.
- [22] C. E. Nahum and H. Cantalloube, "Improvement of Detection Via Data Association," *Proceedings of SPIE*, Vol. 2232, pp. 26-36, 1994.
- [23] R. Mahler, "Unified Data Fusion: Fuzzy Logic, Evidence, and Rules," *Proceedings of SPIE*, Vol.2755, pp. 226-237, 1996.
- [24] R. Deaves and P. Greenway, "An Experimental Evaluation of Distributed Identity Fusion," *Proceedings of SPIE*, Vol. 2355, pp. 74-85, 1994.
- [25] L. A. Klein, "Sensor and Data Fusion Concepts and Applications," *SPIE- The International Society for Optical Engineering*, Bellingham, Washington, 1993.
- [26] D. Avitzour, "A Maximum Likelihood Approach to Data Association," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 28, No.2, April 1992, pp. 560-566.
- [27] J. Roecker, "Multiple Scan JPDA," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 31, No.3, July 1995, pp. 1204-1209.

- [28] A. Edwin and H. Blom, "JPDA Methods Avoiding Track Coalescence," *Proceedings of the 34th Conference on Decision and Control*, Dec. 1995, pp. 2752-2757.
- [29] J. Roecker and G. L. Phillis, "Suboptimal Joint Probabilistic Data Association," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 29, No.2, April 1993, pp. 510-157.
- [30] J. Dezert and Y. Bar-Shalom, "JPDA for Autonomous Navigation," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 29, No.4, Oct. 1993, pp. 1275-1286.
- [31] Y. Bar-Shalom and E. Tse, "Tracking in a Cluttered Environment With PDA," *Automatic*, Vol. II, September 1975, pp. 451-460.
- [32] Chen Ji, H. Leung, Titus LO, J. Litva, and M. Blanchette, "A Modified PDAF in a Real Clutter Environment," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 32, No.1, Jan. 1996, pp. 300-313.
- [33] D. Musicki and R. Evans, "Integrated PDA in Clutter With Finite Resolution Sensor," *Proceedings of the 32nd Conference on Decision and Control*, Dec. 1993, pp. 912-917.
- [34] J. B. Collins and K. Jeffrey Uhlmann, "Efficient Gating in Data Association With Multivariate Gaussian Distributed States," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 28, No.3, July 1992, pp. 909-916.
- [35] D. Musicki, R. Evans, and S. Stankovic, "Integrated PDA," *IEEE Transactions on Automatic Control*, Vol. 39, No. 6, June 1994, pp. 1237-1241.
- [36] D. L. Hall and R. J. Linn, "A Taxonomy of Algorithms for Multisensor Data Fusion," *Proceedings of the 1990 Joint Service Data Fusion Symposium*, Johns Hopkins University, Laurel, Maryland Naval Air Development Center, Warminster, PA, May 1990, pp.593-610.
- [37] Liebetrau and M. Albert, "Measures of Association in the Series: Quantitative Applications in the Social Sciences," *Sage University Publication*, Paper 32, Sage Publications, London, 1984.
- [38] L. A. Zadeh, "Fuzzy Logic," *IEEE Computer*, 21, April 1988, pp.83-93.
- [39] L. A. Zadeh, *Fuzzy Logic for the Management of Uncertainty*, John Wiley and Sons, New York, 1992.
- [40] J. C. Bezdek, *Analysis of Fuzzy Information*, Vol. II, Artificial Intelligence and Decision Systems, CRC Press, New York, 1986.
- [41] L. A. Zadeh, "Fuzzy Sets as a Basis for a Theory of Possibility," *IEEE Computer* 21, *Fuzzy Sets and Systems, International Journal*, Vol. 1, 1978, pp. 3-28.

- [42] M. Delgado and S. Moral, "On the Concept of Possibility-Probability Consistency," *Fuzzy Sets and Systems, International Journal*, Vol. 21, No. 3, March 1987, pp. 311-318.
- [43] J. C. Bezdek, *Pattern Recognition With Fuzzy Objective Function Algorithms*, Plenum Press, New York, 1981.
- [44] J. C. Bezdek and J. C. Dunn, "Optimal Fuzzy Partition: A Heuristic for Estimating the Parameters in a Mixture of Normal Distributions," *IEEE Transactions on Computer*, Vol. C-24, 1975, pp. 835-838.
- [45] R. J. Hathaway, J. C. Bezdek, and W. Pedrycz, "A Parametric Model for Fusing Heterogenous Fuzzy Data," *IEEE Transactions on Fuzzy Systems* 4, pp. 270-281, 1996.
- [46] R. Krishnapuram and J. M. Keller, "A Possibilistic Approach to Clustering," *IEEE Transactions on Fuzzy Systems* 1, pp. 98-110, 1993.
- [47] T. Kovattana, "Theoretical Analysis of Intrusion Alarm Using Two Complementary Sensors," *Proceedings of Carnahan Conference Electronic Crime Countermeasures*, pp. 37-52, USA, April 1973.
- [48] A. Fefjar, "Combining Techniques to Improve Security in Automated Entry Control," *Proceedings of Carnahan Conference on Crime Countermeasures*, p. 89, Abstract only, USA, May 1978.
- [49] S. D. Stearns, "Optimum Detection Using Multiple Sensors," *Proceedings of Carnahan Conference on Security Technology*, Lexington, KY, USA 1983.
- [50] R. Tenney and N. R. Sandell, "Detection With Distributed Sensors," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-17, No. 4, pp. 501-510, July 1981.
- [51] Z. Chair and P.K. Varshney, "Optimal Data Fusion in Multiple-Sensor Detection Systems," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-22, No. 1, Jan. 1986.
- [52] R. Srinivasan, "Distributed Radar Detection Theory," *IEE Proceedings*, Vol. 133, Pt. F. No. 1, pp. 55-60, Feb. 1986.
- [53] S. Thomopoulos, Ramanarayana, and Bougoulas, "Optimal Decision Fusion in Multiple-Sensor Systems," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-23, No. 5 pp. 644-652, 1987.
- [54] L. A. Zadeh, King-Sun Fu, K. Tanaka, and M. Shimura, *Fuzzy Sets and Their Applications to Cognitive and Decision Processes*, San Francisco, New York, Academic Press, 1975.

- [55] H. Zimmermann, L. A. Zadeh, and B. R. Gaines, *Fuzzy Sets and Decision Analysis*. Amsterdam, North-Holland, Elsevier Science, 1984.
- [56] M. R. Civanlar and H. J. Trussell, "Constructing Membership Functions Using Statistical Data," *Fuzzy Sets and Systems, International Journal*, Vol. 18, No. 1, Jan. 1986, pp. 1-13.
- [57] H. Odeberg, "Distance Measures for Fuzzy Sensor Opinions," *Measurement Science and Technology, Formerly Journal of Physics, Scientific Instruments*, Vol. 4, No. 8, Aug. 1993, pp. 808-815.
- [58] R. P. Singh and W. H. Balley, "Fuzzy Logic Applications to Multisensor-Multitarget Correlation," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 33, No. 3, July 1997, pp.752-769.
- [59] W. Wong and R. Brockett, "System With Finite Communication Bandwidth Constraints-Part I: State Estimation Problems," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 42, No. 9, Sept. 1997, pp. 1294-1299.
- [60] Tao Li and I. K. Sethi, "Optimal Multiple Level Decision Fusion With Distributed Sensors," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 29, No. 4, July 1993, pp. 1252-1259.
- [61] D. E. Brown, C. L. Pittard, and A. R. Spillane, "A Simulation-Based Test for Data Association Algorithms" *Proceedings of SPIE*, Vol. 1306, Sensor Fusion III, 1990, pp. 58-68.
- [62] F. Russo and G. Ramponi, "Fuzzy Methods for Multisensor Data Fusion," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 43, No. 2, April 1994, pp. 288-294.
- [63] T. Sudkamp, "On Probability-Possibility Transformation," *Fuzzy Sets and Systems, International Journal*, 51, 1992, pp. 73-81.
- [64] K. Molnar and J. W. Modestino, "Application of the EM Algorithm for the Multitarget/Multisensor Tracking Problem," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 46, No. 1, Jan. 1998, pp.115-128.
- [65] Ashraf Mamdouh Aziz, *Comparative Study of Different Distributed Decision Algorithms in Distributed Sensor Systems*, M. Sc. Thesis, Military Technical College, Cairo, Egypt, 1992.
- [66] Ashraf Mamdouh Aziz, M. ElAyadi, and ElBasiony, "Decentralized Detection of Targets," *Technology and Armament Magazine*, Jan. 1994, Cairo, Egypt.
- [67] Ashraf Mamdouh A. Aziz, "Optimum Signal Processing in Multiple Sensor Distributed Detection Systems," *Magazine of the Cairo University of Engineering*, Cairo, Egypt, 1994.

- [68] Ashraf Mamdouh Aziz, "Toward Global Optimization of Distributed Sensor Detection Systems," *Technology and Armament Magazine*, March 1994, Cairo, Egypt.
- [69] Ashraf Mamdouh Aziz, "Optimum Strategies in Distributed Sensor Detection Systems," *Technology and Armament Magazine*, July 1995, Cairo, Egypt.
- [70] Ashraf Mamdouh Aziz, M. ElAyadi, and ElBasiony, "Applications of Distributed Array Antenna for Detection of Targets," *Technology and Armament Magazine*, Jan. 1994, Cairo, Egypt.
- [71] Ashraf Mamdouh Aziz, M. ElAyadi, and ElBasiony, "Quantitative Evaluation of Global Performance Improvement in Multiple Identical Sensors Distributed Detection Systems," *Proceedings of the Eleventh National Radio Science Conference*, Military Technical College, Cairo, Egypt, 1994.
- [72] Ashraf Mamdouh Aziz, M. ElAyadi, and ElBasiony, "Comparative Study of Global Performance Improvement in Distributed Sensor System," *Proceedings of the Twelfth National Radio Science Conference*, Alexandria University of Engineering, Alexandria, Egypt, 1995.
- [73] M. H. ElAyadi, Ashraf Mamdouh Aziz, and ElBasiony, "An Algorithm for Global Optimization of Distributed Multiple-Sensor Detection Systems Using Neyman-Pearson Strategy," *Signal Processing*, Vol. 51, No. 2, pp. 137-145, June 1996.
- [74] J. Smith, "A Fuzzy Clustering and Superclustering Scheme for Extracting Structure Data," *NRL Report NRL/FR/5740-96-9844*, Naval Research Laboratory, Washington D.C. 20375-5000, Dec. 31, 1996.
- [75] Murali Tummala and Sean A. Midwood, "A Fuzzy Associative Data Fusion Algorithm for VTS " *Technical Report for U.S. Coast Guard, Naval Postgraduate School*, Monterey, CA, Sept. 1997.
- [76] Midwood, Sean A., *A Computationally Efficient and Cost Effective Multisensor Data Fusion Algorithm for the USCG Vessel Traffic Service Systems*, M.S.E.E. Degree Thesis, Naval Postgraduate School, Monterey, CA, Sept. 1997.
- [77] Glenn, Ian N., *Multilevel Data Association for the Vessel Traffic Service System and Joint Maritime Command Information System*, M.S.E.E. Degree Thesis, Naval Postgraduate School, Monterey, CA, Sept. 1995.
- [78] Y. Bar-Shalom, *Multitarget Multisensor Tracking: Applications and Advances*, Vol. I. Norwood, MA, Artech House, 1990.
- [79] Y. Bar-Shalom, *Multitarget Multisensor Tracking: Applications and Advances*, Vol. II. Norwood, MA, Artech House, 1992.

- [80] J. C. Bezdek, *Fuzzy Mathematics in Pattern Classification*, Ph.D. Dissertation, Appl. Math., Cornell Univ., Ithaca, NY, 1973.
- [81] Nikola K. Kasabov, *Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering*, The MIT Press, Massachusetts, London, England, 1996.
- [82] Bart Kosko, *Neural Networks and Fuzzy Systems*, Prentice Hall, England Cliffs, NJ, 1992.
- [83] H.-J. Zimmermann, *Fuzzy Set Theory and its Applications*, Third Edition, Kluwer Academic Publishers, Boston, London, 1996.
- [84] Y. Bar-Shalom and X. Rong Li, *Estimation and Tracking: Principles, Techniques, and Software*, Artech House, Boston, London, 1993.
- [85] R. G. Brown and P. Y. Hwang, *Introduction to Random Signals and Applied Kalman Filtering*, Third Edition, John Wiley Sons, New York, 1997.
- [86] R. T. Antony, *Principles of Data Fusion Automation*, Norwood MA, Artech House, Boston, London, 1995.
- [87] J. Zupan, *Clustering of Large Data Sets*, Researcher Studies Press, New York, 1982.
- [88] H. Charles Romesburg, *Cluster Analysis for Researchers*, Lifetime Learning Publications, London, 1984.
- [89] J. Hartigan, *Clustering Algorithms*, John Wiley and Sons, New York, 1975.
- [90] H. Spath, *Cluster Analysis Algorithms for Data Reduction and Classification of Objects*, John Wiley and Sons, New York, 1980.
- [91] J. Smith, "An Application of Clustering and Speed Discrimination to Tracking", *NRL Report NRL/FR/5740-95-9801*, Naval Research Laboratory, Washington DC 20375-5000, Dec. 1995.
- [92] R. K. Saha and K. C. Chang, "An Efficient Algorithm for Multisensor Track Fusion," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 34, No. 1, pp. 200-210, Jan. 1998.
- [93] Y. Zhang, H. Leung, T. Lo, and John Litva, "An Efficient Decentralized Multi-radar Multitarget Tracker for Air Surveillance," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 33, No. 4, pp. 1357-1363, Oct. 1997.
- [94] B. Zhou and N. K. Bose, "An Efficient Algorithm for Data Association in Multitarget Tracking," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 31, No. 1, pp. 458-468, Jan. 1995.

- [95] Y. Zhang, et al., "Distributed Sequential Nearest-Neighbor Multitarget Tracking Algorithm," *IEEE Proceedings on Radar, Sonar, and Navigation*, Vol. 143, No. 4, pp. 225-260, Aug. 1996.
- [96] L. A. Zadeh, "Outline of a New Approach to the Analysis of Complex Systems and Decision Process," *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 3, No. 1, pp. 28-44, 1973.
- [97] A. Kummert, "Fuzzy Technology Implemented in Sonar Systems," *IEEE Journal of Oceanic Engineering*, Vol. 18, No. 4, pp. 483-490, 1993.
- [98] C. Moore, C. Harris, and E. Rogers, "Utilizing Fuzzy Models in the Design of Estimators and Predictors: An Agile Target Tracking Example," *Proceedings of the 2nd IEEE Conference on Fuzzy Systems*, pp. 679-684, 1993.
- [99] C. Tao, W. Thompson, and J. Taur, "A Fuzzy Logic Approach in Multidimensional Target Tracking," *Proceedings of the 2nd IEEE Conference on Fuzzy Systems*, pp. 1350-1355, 1993.
- [100] S. Mori, C. Chong, T. Tse, and R. Wisher, "Tracking and Classifying Multiple Targets Without a Priori Identification," *IEEE Transactions on Automatic Control*, Vol. AC-31, No. 1, pp. 401-409, May 1986.
- [101] D. Sengupta, et al., "Neural Solution to the Multiple Target Tracking Data Association Problem," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-25, pp. 96-108, Jan. 1989.
- [102] L. A. Zadeh, "The Concept of Linguistic Variable and Its Application to Approximate Reasoning-Parts I, II, III," *Information Science* 8, pp. 301-357, 1975.
- [103] W. Pedrycz, *Fuzzy Control and Fuzzy Systems*, 2nd ed., New York, Wiley, 1993.
- [104] R. J. Hathaway, G. Rogers, J. C. Bezdek, and W. Pedrycz, "Fusing Heterogeneous Fuzzy Data for Clustering," *Proceedings of SPIE*, Vol. 3068, pp 559-568, 1997.
- [105] J. A. Stover, D. L. Hall, and R. E. Gibson, "A Fuzzy Logic Architecture for Autonomous Multisensor Data Fusion," *IEEE Transactions on Industrial Electronics*, Vol. 43, No. 3, pp. 403-410, June.
- [106] D. E. Gustafson and W. Kessel, "Fuzzy Clustering With a Fuzzy Covariance Matrix," *Proceedings of IEEE-CDC*, Vol. 2 (K. S. Fu, ed.), pp. 761-766, IEEE Press, Piscataway, NJ, 1979.
- [107] M. P. Windham, "Cluster Validity for the Fuzzy C-Means Clustering Algorithm," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. PAMI-4, No. 4, July 1982, pp. 357-363.

- [108] M. P. Windham, "Geometrical Fuzzy Clustering Algorithms," *Fuzzy Sets and Systems, International Journal*, Vol. 10, No. 3, July 1983, pp. 271-279.
- [109] J. Fisher and D. P. Casasent, "Fast JPDA Multitarget Tracking Algorithm," *Applied Optics*, 28, pp. 371-376, Jan. 1989.
- [110] B. Zhou and Bose N., "Multitarget Tracking in Clutter: Fast Algorithm for Data Association," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-29, pp. 352-363, April 1993.
- [111] L. A. Zadeh, "Fuzzy Sets," *Information and Control* 8, pp. 338-353, 1965.
- [112] R. A. Singer and A. Kanyuck, "Correlation of Multi-Site Track Data," *IEEE Transactions on Aerospace and Electronic Systems*, AES-6, March 1970, pp. 180-187.
- [113] R. A. Singer and A. J. Kanyuck, "Computer Control of Multiple-Site Track Correlation," *Automatica*, Vol. 7, 1971, pp. 455-463.
- [114] R. A. Singer and K. Behnke, "Real-Time Tracking Filter Evaluation and Selection for Tactical Applications," *IEEE Transactions on Aerospace and Electronic Systems*, AES-7, No.1, Jan. 1971, pp. 100-110.
- [115] D. Willner, B. Chang, and K. P. Dunn, "Kalman Filter Algorithms for a Multi-Sensor System," *Proceedings of IEEE Conference on Decision and Control*, Dec. 1976, pp. 570-574.
- [116] Y. Bar-Shalom, "On the Track-to-Track Correlation Problem," *IEEE Transactions on Automatic Control*, Vol. AC-26, No. 2, April 1981, pp. 571-572.
- [117] Y. Bar-Shalom and Leon Campo, "The Effect of the Common Process Noise on the Two-Sensor Fused Track Covariance," *IEEE Transactions on Aerospace and Electronic Systems*, AES-22, No.6, Nov. 1986, pp. 803-805.
- [118] A. M. Haimovich, J. Yosko, R. Greenberg, M. Parisi, and D. Becker, "Fusion of Sensors With Dissimilar Measurement/Tracking Accuracies," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 29, No.1, Jan. 1993, pp. 245-250.
- [119] R. K. Saha, "Track-to-Track Fusion With Dissimilar Sensors," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 32, No.3, July 1996, pp. 1021-1029.
- [120] K. Chang, R. K. Saha, Y. Bar-Shalom, and M. Alford, "Performance Evaluation of Multisensor Track-to-Track Fusion," *Proceedings of the 1996 IEEE/SICE/RSJ International Conference on Multisensor Fusion and Integration for Intelligent Systems*, 1996, pp. 627-632.

- [121] K. White, I. Dall, and A. Shellshear, "Association of Over-The-Horizon Radar Tracks With Tracks from Microwave Radar and Other Sources," *Proceedings of SPIE*, Vol. 2755, 1996, pp. 335-346.
- [122] M. Mohandes, R. Bonger, and A. Bouzerdoun, "Hierarchical Clustering for OTHR Track Fusion," *Proceedings of Australian Data Fusion Symposium*, ADFS'96, Nov. 1996, pp. 90-93.
- [123] Y. Bar-Shalom, "Redundancy and Data Compression Recursive Estimation," *IEEE Transactions on Automatic Control*, Oct. 1972, pp. 684-689.
- [124] P. R. Kalata, "The Tracking Index: A Generalized Parameter for $\alpha - \beta$ and $\alpha - \beta - \gamma$ Target Trackers," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-20, No.2, March 1984, pp. 174-182.
- [125] J. Stein and S. S. Blackman, "Generalized Correlation of Multi-Target Track Data," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. AES-11, No. 6, Nov. 1975, pp. 1207-1217.
- [126] W. Guo-Hong, He You, Z. Gao, and L. Ya-Jun, "Improved Data Association of ESM Measurements With Radar Tracks," *Proceedings of the 1997 Radar Conference*, Oct. 1997, pp. 648-652.
- [127] W. Guozhong, et al., "A New Radar ESM Correlation Algorithm in Multisensor Data Fusion," *Proceedings of the 1996 Radar Conference*, Oct. 1996, pp. 774-750.
- [128] R. Palm, "Scaling of Fuzzy Clustering Controller Using the Cross-Correlation," *IEEE Transactions on Fuzzy Systems*, Vol. 3, No. 1, Feb. 1995, pp. 116-123.
- [129] J. Roecker and G. L. Phillis, "Suboptimal Joint Probabilistic Data Association", *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 29, No.2, April 1993, pp. 510-517.
- [130] J. Llinas and D. Hall, "An Introduction to Multisensor Data Fusion," *Proceedings of the 1998 IEEE International Symposium on Circuit and Systems*, Vol. 6, Monterey, CA, June 1998, pp. 537-540.
- [131] Sean A. Midwood, Ian N. Glenn, and Murali Tummala, "A Multi Sensor Data Fusion Algorithm for the USCG's Vessel Traffic Services System," *Proceedings of the 1998 IEEE International Symposium on Circuit and Systems*, Vol. 6, Monterey, CA, June 1998, pp. 545-548.
- [132] A. Cameron, G. Haberman, M. Mohandes, and R. E. Bogner, "Modeling OTHR Tracks for Association and Fusion," *Proceedings of the 1996 IEEE National Conference on Radar*, May 1996, pp. 100-105.
- [133] R. K. Saha, "Effect of Cross-Correlation on Track-to-Track Fusion," *Proceedings of SPIE*, Vol. 2235, 1994, pp. 474-485.

- [134] A. T. Alouani and T. R. Rice, "Performance Analysis of an Asynchronous Track Fusion and Architecture," *Proceedings of SPIE*, Vol. 3068, 1997, pp. 194-205.
- [135] E. Shahbazian, M. Simard, and S. Bourassa, "Implementation Strategies for the Central Level Multi-Hypothesis Tracking Fusion With Multiple Dissimilar Sensors," *Proceedings of SPIE*, Vol. 1955, 1993, pp. 78-88.
- [136] R. K. Saha, K. C. Chang, and M. M. Kokar, "Fusion of Synchronous Tracks," *Proceedings of SPIE*, Vol. 3068, 1997, pp. 206-217.
- [137] K. C. Chang, R. K. Saha, and Y. Bar-Shalom, "On Optimal Track-to-Track Fusion," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 33, No. 4, Oct. 1997, pp. 1271-1276.
- [138] R. Robert, J. Carson, M. P. Meyer, and D. J. Peter, "Fusion of IFF and Radar Data," *Avionic Systems Conference*, Oct. 1997, pp. 5.3-9-15.
- [139] C. Tao, J. S. Taur, H. C. Kuo, J. Wu, and W. E. Thompson, "An Estimator Based on Fuzzy If-Then Rules for the Multisensor Multidimensional Multitarget Tracking Problem," *Proceedings of the 1994 IEEE World Congress on Computational Intelligence*, June 1994, Vol. 3, pp. 1543-1548.
- [140] R. Lobbia and M. Kent, "Data Fusion of Decentralized Local Tracker Outputs," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 30, No. 3, July 1994, pp. 787-799.
- [141] M. de Feo, A. Graziano, R. Miglioli, and A. Farina, "Correlation: Performance Comparison," *IEE Proceedings on Radar, Sonar and Navigation*, Vol. 144, No. 2, April 1997, pp. 49-56.
- [142] S. Deb, K. Pattipati, and Y. Bar-Shalom, "A Multisensor-Multitarget Data Association Algorithm for Heterogeneous Sensors," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 29, No. 2, April 1993.
- [143] F. R. Castella, "Theoretical Performance of a Multisensor Track-to-Track Correlation Techniques," *IEE Proceedings on Radar, Sonar and Navigation*, Vol. 142, No. 6, Dec. 1995, pp. 281-285.
- [144] J. Collins and J. Uhlmann, "Efficient Gating in Data Association With Multivariate Gaussian Distributed States," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 28, No. 3, July 1992, pp. 909-916.
- [145] J. A. Roecker, "A Class of Near Optimal JPDA Algorithms," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 30, No. 2, April 1994, pp. 504-509.

- [146] X. Rong Li and Y. Bar-Shalom, "Tracking in Clutter With Nearest-Neighbor Filters: Analysis and Performance," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 32, No. 3, July 1996, pp. 995-1010.
- [147] R. J. Pawlak and A. A. Beex, "Fusion Technique for Multisensor Track Initiation," *IEE Proceedings on Radar, Sonar and Navigation*, Vol. 142, No. 5, Oct. 1995, pp. 225-231.
- [148] Y. Bar-Shalom and X. Rong Li, "Multitarget Multisensor Tracking: Principles and Techniques," *IEEE AES Systems Magazine*, Feb. 1996, pp. 41-44.
- [149] Y. Bar-Shalom and X. Rong Li, "Multitarget Multisensor Tracking: Principles and Techniques," *IEEE Control Systems Magazine*, Feb. 1996, pp. 93-96.
- [150] T. Wigren, et al., "Operational Multisensor Tracking for Air Defense," *First Australian Data Fusion Symposium*, ADFS'96, pp. 13-18.
- [151] M. Krieg, et al., "Track Fusion in the Presence of an Interference," *Forth International Symposium on Signal Processing and its Applications*, 1996, pp. 192-195.
- [152] A. T. Alouani and T.R. Rice, "On Optimal Asynchronous Track Fusion," *First Australian Data Fusion Symposium*, ADFS'96, pp. 147-152.
- [153] M. Krieg and D. Gray, "Radar and Optimal Track Fusion Using Real Data," *First Australian Data Fusion Symposium*, ADFS'96, pp. 25-30.
- [154] C. Schleifeer, et al., "High Performance Multitarget-Multisensor Tracking for a Geographically Distributed Systems," *Proceedings of the 1995 IEEE International Symposium on Intelligent Control*, Aug. 1995, pp. 483-488.
- [155] M. Krieg and D. Gray, "Comparison of Probabilistic Least Square and Probabilistic Multi-Hypothesis Tracking Algorithms for Multi-Sensor Tracking," *1997 IEEE International Conference on Acoustic, Speech, and signal Processing*, April 1997, pp. 21-24.
- [156] S. Blackman and N. Banh, "Track Association Correction for Bias and Missing Data," *Proceedings of SPIE*, Vol. 2235, 1994, pp.529-539.
- [157] K. C. Chang and Y. Bar-Shaloom, "FUSEDAT: A Software Package for Fusion and Data Association and Tracking With Multiple Sensors," *Proceedings of SPIE*, Vol. 2235, 1994, pp. 497-506.
- [158] R. E. Gibson and D. L. Hall, "An Autonomous Fuzzy Logic Architecture for Multisensor Data Fusion," *IEEE International Conference on Multisensor Data Fusion*, MFI'94, 1994, pp. 143-150.

- [159] B. Qiu and D. Zhang, "An Approach to Multisensor Multitarget Tracking," *Proceedings of the IEEE International Conference on Industrial Technology*, 1994, pp. 4109-413.
- [160] H. Wenlong, et al., "A Probabilistic Data Association Algorithm for Multisensor Multitarget Tracking," *Proceedings of the 1996 International Conference on Radar*, 1996, pp. 475-479.
- [161] S. Xiaoquan, et al., "Data Association in Multitarget Tracking With Multisensor," *Proceedings of the IEEE 1997 National Conference on Aerospace and Electronics*, Vol. 2, 1997, pp. 884-889.
- [162] D. Buede, "Examination of the Fuzzy Subsethood Theorem for Data Fusion," *Proceedings of the 1994 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, MFI'94, Las Vegas, NV, Oct. 1994, pp. 430-434.
- [163] T. Kohonen, "The Self-Organizing Map," *Proceedings of the IEEE*, Sept. 1990, pp. 1464-1497.
- [164] T. Kohonen, *Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering*, Massachusetts Institute of Technology, 1996.
- [165] T. Kohonen, "Physiological Interpretation of the Self-Organizing Map Algorithm," *Neural Network*, Vol. 6, 1993, pp. 895-905.
- [166] J. C. Bezdek, *Fuzzy Models for Pattern Recognition*, New York, IEEE Press, 1992.
- [167] J. C. Bezdek, *Analysis of Fuzzy Information*, Vol. 3, Boca Raton, FL, CRC Press, 1987.
- [168] R. N. Dave, "Fuzzy Shell Clustering and Applications to Circle Detection in Digital Images," *International Journal of Gen. Sys.*, No. 16, 1990, pp. 343-355.
- [169] B. Everett, *Cluster Analysis*, Academic Press, New York, 1980.
- [170] S. W. Balakrishnan and B. D. Tapley, "Multitarget Classification and Estimation Using Clustering Technique," *Journal of Guidance*, Vol. 1, Jan-Feb 1990, pp. 121-127.
- [171] J. Stein and S. S. Blackman, "Generalized Correlation of Multi-Target Track Fusion," *IEEE Transactions on Aerospace and Electronic Systems*, AES-11, Nov. 1975, pp. 1207-1217.
- [172] R. G. Sea, "Optimal Correlation of Sensor Data With Tracks in Surveillance Systems," *Proceedings of the Sixth International Conference on Systems Sciences*, Jan. 9-11, 1973, Honolulu, pp. 424-426.

- [173] A. Graziano, R. Miglioli, and A. Farina, "Multiple Hypothesis Tracking vs Kalman Filter With Nearest-Neighbor Correlation: Performance Comparison," *AGARD Conference Proceedings*, No. 557, Lisbon, May 1995, pp. 25/1-25/11.
- [174] J. O. Coleman, "Discriminations for Assigning Passive Bearing Observations to Radar Targets," *Proceedings of 1980 IEEE International Conference on Radar*, Washington, DC, pp. 361-365.
- [175] D. E. Brown, C. L. Pittard, and W. N. Martin, "Neural Network Implementation for Data Association Algorithms for Sensor Fusion," *Proceedings of SPIE*, Vol. 1100, Sensor Fusion II, 1989, pp. 126-135.
- [176] D. Dubois and H. Prade, *Fuzzy Sets and Systems: Theory and Applications*, New York, London, Toronto, Academic Press Inc., 1980.
- [177] M. R. Anderberg, *Cluster Analysis for Applications*, New York, Academic Press, 1973.
- [178] I. W. Dall and A. J. Shellshear, "Evaluation of Model Based Fusion Algorithm With Multi-Mode OTHR Data," *IEEE Asilomar Conference on Signals, Systems, and Computers*, 1993.
- [179] J. M. Mendel, "Fuzzy Logic Systems for Engineering: A Tutorial," *Proceedings of the IEEE*, Vol.83, No.3, March 1995.
- [180] D. L. Hall and R. J. Linn, "A Taxonomy of Algorithms for Multisensor Data Fusion," *Proceedings of the 1990 Joint Service Data Fusion Symposium*, Johns Hopkins University, Laurel, Maryland Naval Air Development Center, Warminster, PA, May 1990, pp. 593-610.
- [181] Eugenio S. Anzano, *Fuzzy Clustering Means Algorithm for Track Fusion in U.S. Coast Guard Vessel Traffic Services Systems*, M.S.E.E. Degree Thesis, Naval Postgraduate School, Monterey, CA, June 1999.
- [182] J. Manyika and H. Durrant-Whyte, *Data Fusion and Sensor Management: a Decentralized Information-Theoretic Approach*, Chichester, West Sussex, Ellis Horwood, 1994.
- [183] Abdel-Aziz Al-Bassiouni, *Optimum Signal Processing in Distributed Sensor Systems*, Ph.D. Dissertation, Naval Postgraduate School, Monterey, CA, 1987.
- [184] Ashraf Mamdouh A., Murali Tummala, and Roberto Cristi, "An Efficient All-Neighbor Fuzzy Association Approach in Distributed Multisensor-Multitarget Environment," *Proceedings of the 3rd IEEE/IMACS International Multiconference on Circuits, Systems, Communications, and Computers, CSCC'99*, Athens, Greece, July 1999.

- [185] M. I. Skolnik, *Introduction to Radar Systems*, New York, McGraw-Hill, 1980.
- [186] Robert G. Hutchins, *Optimal Estimation, Kalman Filtering, and Target Tracking* (Course Notes), Naval Postgraduate School, Monterey, CA, March 1997.
- [187] A. Papoulis, *Probability, Random Variables, and Stochastic Processes*, New York, McGraw-Hill, 1991.
- [188] A. Leon-Garcia, *Probability and Random Processes for Electrical Engineering*, CA, Addison-Wesley Company, 1994.
- [189] J. L. Devore, *Probability and Statistics for Engineering and the Sciences*, SF, Wadsworth, 1995.
- [190] B. V. Dasarathy, *Decision Fusion*, CA, IEEE Computer Society Press, 1994.
- [191] R. N. McDonough and A. D. Whalen, *Detection of Signals in Noise*, CA, Academic Press, 1995.
- [192] D. Hanselman and B. Littlefield, *Mastering Matlab, a Comprehensive Tutorial and Reference*, N. J., Prentice-Hall, 1996.
- [193] Ashraf Mamdouh Aziz, "Multiple-Sensor Distributed Detection Systems With Data Fusion," *Proceedings of the 13th IEEE SP Society and EURASIP International Conference on Digital Signal Processing*, Santorini, Greece, July 1997.
- [194] Ashraf Mamdouh Aziz, Murali Tummala, and Roberto Cristi, "Optimal Data Fusion Strategies Using Multiple-Sensor Detection Systems," *Proceedings of the 31st IEEE Asilomar Conference on Signals, Systems, and Computers*, CA, USA, Nov. 1997.
- [195] Ashraf Mamdouh Aziz, Roberto Cristi, and Murali Tummala, "Applications of Data Fusion in Centralized and Decentralized Distributed Detection Systems," *Proceedings of the IEEE and IASTED International Conference on Image and Signal Processing*, SIP 97, New Orleans, Louisiana, USA, Dec. 1997.
- [196] Ashraf Mamdouh Aziz, Roberto Cristi, and Murali Tummala, "A Time Series of Decisions Approach in Detection Systems," *Proceedings of the 32nd IEEE Asilomar Conference on Signals, Systems, and Computers*, CA, USA, Nov. 1998.
- [197] Ashraf Mamdouh Aziz, Murali Tummala, and Roberto Cristi, "Fuzzy Logic Data Association Approach In Multisensor-Multitarget Data Fusion," *Proceedings of the IEEE IASTED International Conference on Signal and Image Processing*, Las Vegas, NV, USA, Oct. 1998.

- [198] Ashraf Mamdouh Aziz, Roberto Cristi, and Murali Tummala, "An Efficient All-Neighbor Fuzzy Association Approach in Distributed Multisensor-Multitarget Environment," *Proceedings of the 3rd IEEE/IMACS International Multiconference on Circuits, Systems, Communications, and Computers, CSCC'99*, Athens, Greece, July 1999.
- [199] Ashraf Mamdouh Aziz, Roberto Cristi, and Murali Tummala, "Fuzzy Track-to-Track Association and Track Fusion Approach in Distributed Multisensor-Multitarget Multiple-Attribute Environment," Submitted to *Signal Processing*, May 1999.
- [200] Ashraf Mamdouh Aziz, Murali Tummala, and Roberto Cristi, "An Efficient Measurement-to-Track Association Approach," Submitted to *IEEE AES*, June 1998.
- [201] Ashraf Mamdouh Aziz, Murali Tummala, and Roberto Cristi, "Probabilistic Data Association Approach in Distributed Multisensor-Multitarget Tracking Systems," *Recent Advances in Signal Processing and Communications, WSES Press and World Scientific Publishing Company*, Athens, July 1999.
- [202] Ashraf Mamdouh Aziz, Murali Tummala, and Roberto Cristi, "Fuzzy Logic Data Correlation Approach In Multisensor-Multitarget Tracking Systems," *Signal Processing*, Vol. 76, No. 2, pp. , July 1999.

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